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Autonomous Solutions in Servitization

A Comprehensive Research Analysis

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ABSTRACT:

In this research, a systematic literature review of the autonomous solution in servitization has been conducted. As the world is shifting towards more artificial intelligence, the need for self-driven optimised service is becoming more demanding day by day. Servitization happens when manufacturing companies change from only selling products to also offering services. Instead of just making and selling things, they add services to improve their offerings. To provide better service, continuous monitoring of the product is essential. Instead of monitoring the service manually, it is required to monitor continuously for enabling the digital business service efficiently. The continuous monitoring service will give real time data of the product which will help the company to provide more value to customers and create new business opportunities.

The integration of autonomous solutions and servitization requires an intensive analysis of current progress of the digital business and technology research for a better understanding of the technology and business models. For this purpose, research articles have been accumulated from different sources and the analysis has been performed using data text mining approach. Data text mining was used because it plays an important role in extracting valuable insights from service interactions, improving decision-making, and optimizing service performance. We tried to filter relevant studies, identify trends, and gain insights for servitization and autonomous solutions using semi-automated tools and algorithms using dynamic topic modeling.

This research explores the role of autonomous technologies in servitization, their impact on business performance, and the research gap associated with implementation. Additionally, technology readiness level measurement has been used in this research to know about the research stage of each cluster. Technology readiness level helps to evaluate the maturity and readiness for deployment in servitization models. The findings highlight the strategic importance of autonomous solutions in reshaping the manufacturing industry.

KEYWORDS: Autonomous Solutions, Data Text Mining (DTM), Technology Readiness Level (TRL), Servitization, Artificial Intelligence (AI), Machine Learning, Term Frequency-Inverse Document Frequency (TF-IDF), BERT.

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Abbreviations

TF-IDF: Term Frequency-Inverse Document Frequency

LDA: Latent Dirichlet Allocation

TRL: Technology Readiness Level

BERT: Bidirectional Encoder Representations from Transformers

UMAP: Uniform Manifold Approximation and Projection

t-SNE: t-Distributed Stochastic Neighbor Embedding

1. Introduction

Integrating autonomous solutions into servitization constitutes an important step in service oriented business models transforming the traditional product centric way of business to value oriented systems, in which continuous services and customization are the focus (Frandsen et al., 2022; Leminen et al., 2022). Autonomous solutions are systems, or technologies, that run on a minimum of human intervention, and that may incorporate AI, robotics, and machine learning (Campbell et al., 2010; Fritschy & Spinler, 2019; Van Brummelen et al., 2018) which include self-driving vehicles, automated production lines, and intelligent inventory management which increases efficiency. It cuts human error and improves operational scalability (Bridgelall & Stubbing, 2021). Servitization is a transformative business strategy for companies to go from traditional product sales to provide the service of integrated product and service to increase the customer value with continuous and support solutions (Kohtamäki et al., 2020; Rabetino et al., 2021). In many industries, servitization is an increasingly important strategy (Kohtamäki et al., 2022), where companies use advanced technology, including AI driven predictive analytics, autonomous systems and IoT enabled monitoring (Naik et al., 2020; Rymaszewska et al., 2017) to increase operational efficiency, improve customer engagement and streamline processes (Sjödin et al., 2023; Thomson et al., 2022).

In this study, a holistic review of the thematic clusters of the autonomous solution in servitization field is undertaken, based on data text mining (Blei & Lafferty, 2006) and Technology Readiness Level (TRL) (Arnouts et al., 2022; Parasuraman, 2000) analysis of the research maturity and evolutionary progress. A data text mining approach was used to analyze research abstracts and to cluster them according to relevant keywords (Rabetino et al., 2021). The clustering has been done using two new technique BERT (Bidirectional Encoder Representations from Transformers) and TR-IDF (Term Frequency-Inverse Document Frequency) along with t-sne and UMAP.

The evolutionary trajectory of these clusters provides key insights into the broader landscape of the autonomous servitization. We tried to map how thematic areas are positioned relative to each other, and how clusters work and mutually reinforce each other by dynamic topic modeling and technology readiness level. This study aims at providing a structure means for understanding autonomous servitization's research landscape by examining the interrelation of these thematic clusters and evolution.

1.1 Background of the Study

Autonomous solutions refer to a system's ability to perform tasks independently under uncertainties. This involves scene recognition, path planning, decision-making, and execution without human intervention (Antsaklis & Rahnama, 2018). One of the most widely visible applications of autonomous solutions is self-driving vehicles. The system uses Artificial Intelligence for recognition of scenes as well as path planning and decision-making functions. They are designed to navigate and make decisions in complex environments. They strictly maintain traffic the laws and ensuring passenger safety properly (Hussain & Zeadally, 2019; Kato et al., 2015). Autonomous robotics systems are another common autonomous solution which is used in industrial manufacturing, healthcare, and service industries. These robots operate in dynamic environments, performing tasks like assembly, monitoring, and delivery, while adapting to real-time changes. These systems minimize human error, especially in high-risk environments like driving or hazardous industries (Rajabli et al., 2021).

Servitization refers to the transformation of manufacturing firms from purely product-based businesses to those that integrate services into their offerings. The companies offer additional services like maintenance, remote monitoring and training to create extra value for the product (Kohtamäki et al., 2019). Servitization often leads to the emergence of Product-Service Systems (PSS), where the service and product are inseparably linked. Firms must shift their business models and corporate culture to align with service-oriented value creation (Kohtamäki et al., 2021). Servitization is a strategic evolution that allows manufacturing firms to create long-term value by integrating services with their products.

In the digital age, servitization has evolved to include digital components, leading to the concept of digital servitization. A recent trend is integrating servitization with digital technologies like AI, IoT and other data analytics (Kohtamäki et al., 2021). With digital transformation playing a larger part in servitization, 'Digital Servitization' has emerged with manufacturers using smart, connected products to provide better services. It enables firms to provide solutions that minimize product performance and predict maintenance, thereby reducing operational costs for customers (T. S. Baines et al., 2009; Frank et al., 2019; Raddats et al., 2019).

Autonomous solutions transform industries by delivering innovative and efficient approaches to resolve complex challenges throughout various sectors. In transportation, Waymo's self-driving cars have achieved significant milestones by logging millions of miles on public roads, showcasing their capabilities in urban and highway environments (Kato et al., 2015). Similarly, the Navya Autonomous Shuttle, an eco-friendly and driverless autonomous bus, is enhancing public transport systems in cities like Lyon, France (Hussain & Zeadally, 2019). Through Prime Air Amazon pioneers drone operation for thirty-minute package delivery to transform next-mile shipment approaches (Rajabli et al., 2021).

Industrial automation company ABB Robotics uses robotic arms to modernize manufacturing operations through material handling applications that excel in automotive assembly workflow (Muñoz et al., 2019). In the mining sector, Rio Tinto employs autonomous haul trucks in Australia to enhance efficiency and safety in ore transportation (Wong et al., 2018). Technological advancements in healthcare include products such as the da Vinci Surgical System that performs minimally invasive surgical procedures for prostatectomy and heart valve repair both accurately and speed up patient recovery. The diagnostic power of Google's AI system improves through its analysis of retinal images to find diabetic retinopathy with exceptional precision (Antsaklis & Rahnama, 2018). The farming industry has integrated autonomy with tools such as John Deere's Autonomous Tractor (Hussain & Zeadally, 2019) alongside DJI's agricultural drones (Rajabli et al., 2021) that bring AI-powered field preparation and field analysis functions.

1.2 Research Gap

1.2.1 Business Models and Market Formation for Autonomous Servitization

In the recent years research in business models and servitization has grown tremendously, however some areas are yet unexplored specifically in the digitalization context. One of the key research gaps lies in the integration of Industry 4.0 with servitization. There are lot of technologies like IoT, AI and other predictive analytics are often citing as enablers. But there is a lack of structure frameworks guidelines about the integration of these tools into service-oriented business models (Meindl et al., 2021). While AI and big data analytics have been widely discussed in marketing and business development, the customer behaviour analysis should be examined more (Chiu & Chuang, 2021).

Another key area requiring further exploration is data-driven business model innovation in servitization. Along with rising importance of data in predictive maintenance, customer engagement, and value co-creation, there is a need to understand how firms can monetize service-based data streams. It should lead to research on embedding an AI-driven decision making within servitization models that can mitigate risks to cybersecurity, data privacy and ethical AI practice (Saura et al., 2023). Without appropriate level sets, companies may not fully exploit such potential of data-driven servitization.

1.2.2 Technological Advancements and Integration

Smart Product-Service Systems (PSS) is emerging as a key concept in modern servitization models. The evolution of Smart PSS presents a research gap. There is limited knowledge on how firms can transition from traditional product-based offerings to smart, connected service ecosystems driven by IoT, AI, and cloud computing (Di Vaio et al., 2020). Wang et al. (2021) propose a graph-based requirement elicitation model for

Smart PSS. But it does not fully address how businesses should dynamically adjust services based on real-time insights from IoT sensors and customer interactions (Z. Wang et al., 2021). There should be more research on how firms can collaborate within digital platforms and multi-stakeholder ecosystems to successfully implement autonomous servitization models (Sandvik et al., 2024).

AI and big data analytics are underutilized in servitization models. Tao and Qi (2019) discuss the role of AI and cloud computing in Smart PSS. But they did not answer about how small and medium enterprises can affordably implement the new technologies (Tao & Qi, 2019). There are a lot of studies on operational efficiency and predictive analysis, but a few studies on monetizing service based data streams (Qiu et al., 2015). Moreover, Liu et al. (2020) suggest that machine learning and big data could enhance servitization business models. But we cannot see that current studies provide any concrete strategies for leveraging these technologies for value creation (C. Liu et al., 2020).

1.2.3 Regulatory and Ethical Challenges

The adoption of AVS-based services is influenced by consumer trust and acceptance. To understand how companies can build consumer confidence in digital servitization business models given the safety critical nature of the applications like passenger transport and last mile delivery, more research is required (Leminen et al., 2022). Despite growing interest in autonomous solutions, there is insufficient research on how regulatory policies, ethical considerations, and liability issues affect digital servitization business models. Future studies should investigate legal frameworks that govern AVS-based service ecosystems. Research is also needed to explore how businesses can effectively monetize service-based data streams. Consumer perceptions of AI-driven servitization, personalized services, and data privacy concerns have not been studied enough. Though companies are using different AI tools for decision-making, there is a gap in understanding about customer trust and engagement (Garbuio & Lin, 2019; Saura et al., 2024).

The widespread adoption of servitized autonomous solutions threatens traditional job roles (Gehlken & Brümmerstedt, 2019). Machine learning models used in decision making may introduce bias in decision making and discriminate transportation accessibility and pricing models. More research is needed to ensure fairness and transparency in these systems (Beck et al., 2022). Autonomous servitization models rely on cloud computing and IoT infrastructure. Security vulnerabilities in these systems can result in service disruptions, data breaches, or even cyberattacks. Research is needed on how cybersecurity measures should be integrated into servitization frameworks (Fraunhofer CML, 2019).

1.2.4 Sustainability and Autonomous Servitization

Servitization is often linked to sustainability. But there is limited evidence on the carbon footprint, resource efficiency, and long-term environmental impact of autonomous servitization models. Integrating economic, environmental, and social aspects of autonomous servitization in current research is still not achieved (Ghzizal et al., 2020). For the sake of sustainability, Ghosh et al. (2023) discuss consumer preferences for refurbished products. But there is limited research on how businesses can incorporate servitization to optimize sustainability-driven services (Ghosh et al., 2023). According to Beck et al. (2022), it is imperative to explore how these models can adapt to uncertainties in the market, changes in regulation, global disruptions (Beck et al., 2022).

1.3 Research questions

Autonomous solutions in servitization arises a lot of complexity as it is still in the beginning phase of implementation. So, there will be lots of questions regarding this issue. We will not be able to discuss all of those. We will focus a few questions here on our research.

RQ1: How the literature of autonomous solutions is integrated into servitization across various industries, and what are the dominant themes over time?

RQ2: What are the key thematic clusters in autonomous servitization research, and how have they evolved over the past decade?
RQ3: How does the technology readiness level (TRL) vary across different clusters of autonomous solutions in servitization?
RQ4: What are the critical gaps in the current literature on autonomous solutions in servitization and how can interdisciplinary approaches or novel methodologies improve the adoption and efficacy of autonomous solutions in servitization?

This study aims to systematically analyze and address these research questions by exploring existing literature, identifying key thematic clusters, assessing technological readiness levels, and highlighting critical gaps in autonomous servitization research.

2. Research Methodology

This study employs an advanced bibliometric approach to identify latent research topics, interdisciplinary patterns, and the technological maturity of identified domains. Through a data topic modeling technique, the study systematically maps out complex interconnections in the literature and assesses the adoption and maturity levels of relevant technologies via Technology Readiness Levels (TRL). After that the research demonstrates the thematic revolution of the clusters and their trends over time, also the alignment of the thematic evolution with the technology readiness level.

In this study, data text mining (Blei & Lafferty, 2006) was conducted using Python to extract and analyze all relevant keywords from journal articles using the method of co-occurrence analysis, targeting the most significant trends. Using these keyword co-occurrences, VOSviewer was then used to create a network of keywords that represent thematic clusters via frequently appearing terms in many journals. This approach clusters journals based on common keywords found, and reveals the main research focuses and connections among literature. That includes reading abstracts into a data structure and then defining clusters with special keywords. Finally, we apply keyword matching algorithms to assign a cluster to each abstract.

Technology Readiness Level (TRL) provides a structured framework to evaluate maturity (Parasuraman, 2000). We have used semi-automated techniques to classify the TRL distribution. TRL has four categories, TRL 1-3, TRL 4-5, TRL 6-7 and TRL 8-9. At the first we tried natural language processing (NLP) techniques to automate the initial classification. By using text analysis and rule-based algorithms, we assign the articles into the initial category. Search terms like basic research, pilot study or commercial implementation and so on were used to identify the category. But by using this technique, all the paper were not correctly assigned to each cluster. So, we manually verify whether they were assigned correctly or not. This ensures the accuracy of the categories within the six clusters. Articles without sufficient textual indicators for automated classification were entirely categorized manually. The classified articles were then grouped to study TRL distribution within clusters (Arnouts et al., 2022). Visualizations, such as grouped bar charts, were used to emphasize the readiness and stability technological solutions in each of the considered themes and to identify patterns, gaps, and opportunities for further research or commercialization efforts (Carmack et al., 2017).

2.1 Creating the article dataset

The systematic literature reviews on servitization for this study were analyzed to create the following comprehensive search query string. The search tool used for this study was Elsevier's Scopus as one of the best sources for finding peer reviewed scholarly articles (Kohtamäki et al., 2019; Rabetino et al., 2021).

The first string was used "Autonomous Systems*" OR "Autonomous Vehicles*" OR "Self-Driving Cars*" OR "Unmanned Aerial Vehicles*" OR "Autonomous Navigation*" OR "Artificial Intelligence*" OR "Machine Learning*" OR "Neural Networks*" OR "Deep Learning*" OR "Computer Vision*" OR "Advanced Driver Assistance Systems*" OR "ADAS*" OR "Sensor Fusion*" OR "LIDAR*" OR "Simultaneous Localization and Mapping*" OR "SLAM*" OR "Autonomous Control Systems*" OR "Reinforcement Learning*" OR "Real-Time Systems*" OR "Autonomous Underwater Vehicles*" OR "Swarm Robotics*" OR "Multi-Agent Systems*" OR "Intelligent Systems*" OR "Robotic Process Automation*" OR "Automation*" OR "AI".

The second string was needed to relate it with autonomous solutions. So the second string was "Product Service System" OR "Product Service Innovation" OR "Servitization" OR "PSI" OR " Product-based service" OR "PSS" OR "servitiz*" OR "Business Model Innovation" OR "servitis*" OR "service modularization" OR "smart service" OR "AI-Driven Services" OR "productization" OR "Service Automation" OR "Service Innovation" OR "Business Model" OR "service supporting products" OR "service supporting processes" OR "services supporting clients" OR "service-driven manufacturing" OR "servicization" OR "service strategy" OR "service dominant logic" OR "product-oriented services" OR "value-added solutions" OR "industrial service offering" OR "industrial service business" OR "customized solutions" OR "customised solutions" OR "servicising" OR "servicizing" OR "servicisation" OR "servicification" OR "service addition" OR "business solution" OR "service package" OR "product service bundling" OR "product-related services" OR "operational services" OR "integrated product and service offering" OR "customer support service" OR "post-sales service" OR "after-sales service" OR "advanced services" OR "product-service system" OR "product service system" OR "product service system" OR "service engineering" OR "result-oriented services" OR "product life-cycle services" OR "experiential services" OR "product-based service" OR "productization" OR "customer-centric" OR "customer care service" OR "service agreement" OR "process related services" OR "performance services" OR "outsourcing services" OR "customer solutions" OR "service management" OR "industrial services" OR "product/service offering".

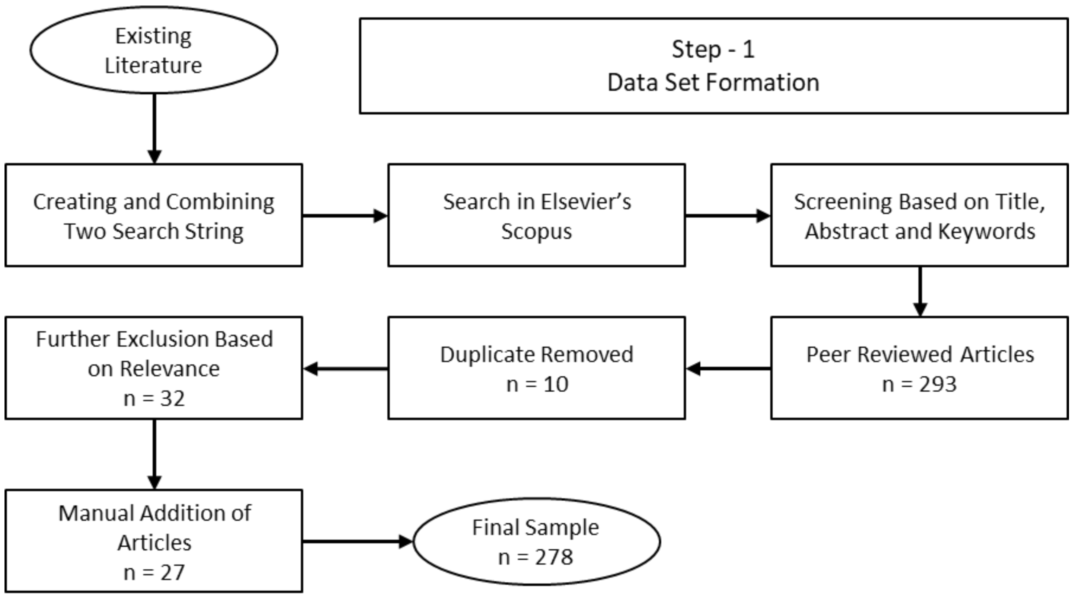

Figure 1: Flowchart of formation of dataset

Figure 1 shows that such an initial search by title, abstract and keywords, in the Scopus database, yields publications. The results were refined and filtered to the specific select subject areas of articles. Then, manually, the selected articles were reviewed, and those publications that did not correspond to the finalized dataset were excluded.

2.2 TF-IDF and t-SNE Based Clustering

Term Frequency (TF) counts how often a word appears in a document. Inverse Document Frequency (IDF) weighs words based on how unique they are across documents. It converts raw text into a numerical matrix. So, TF-IDF vectorization was used to calculate how much significance each term has in each document in relation to frequency and importance between the whole datasets (Lan, 2022). For visualization of the complex thematic relationships existing within the dataset, we applied t-SNE (t-distributed Stochastic Neighbor Embedding) reducing the high dimensional TF-IDF data into three dimensions (H. Liu et al., 2021).

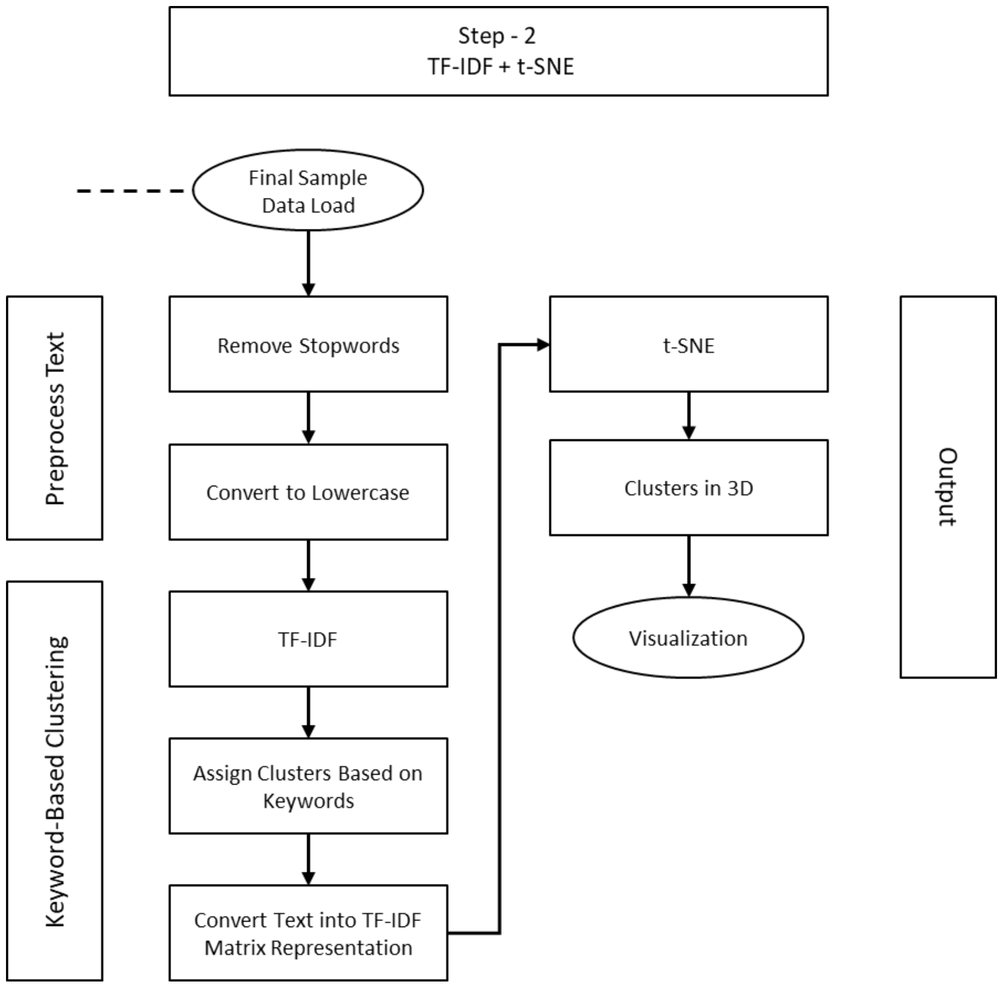

Figure 2. Flowchart for TF IDF.

The processed data from step 1 has been used to analyze the text from the articles in step 2. The process in figure 2 starts with loading the data. Once the data is loaded, text preprocessing is performed to clean and standardize the text. At the first step, common words that do not add significant meaning were removed which has been illustrated as remove stop words. The second stage of preprocessing data is to convert the data to lowercase to ensure uniformity. Further, the cleaned text is converted into a TF-IDF. It helps in transforming textual data into a numerical format that makes it suitable for further analysis. Once the text is transformed, t-SNE (t-distributed Stochastic Neighbor Embedding) is applied. It reduces the dimensionality to visualize high-dimensional data in a lower-dimensional space.

2.3 BERT-Based Topic Clustering

BERTopic represents a topic modeling approach which utilizes BERT along with other transformer-based embeddings for producing reasonable human-interpretable topics from text content. By implementing word embeddings and clustering algorithms BERTopic surpasses the weaknesses of LDA (Latent Dirichlet Allocation).

The data processing in figure 3 starts with loading the information from step 1 followed by text preprocessing that performs two operations: stopping words removal and lowercasing the text to establish uniformity. The next process uses BERT-based feature extraction to transform each abstract into high-dimensional BERT embeddings through the utilization of a pretrained BERT model. After normalization, the embeddings go through storage awaiting further analysis. UMAP (Uniform Manifold Approximation and Projection) is applied to the high dimensional embeddings for reduction in dimensionality of embedding, while keeping their structure meaningful.

After dimensionality reduction, the topic clusters are detected using HDBSCAN (Hierarchical Density Based Spatial Clustering of Applications with Noise) according to density. HDBSCAN is an advanced clustering algorithm that improves upon DBSCAN by automatically determining the number of clusters and handling outliers effectively. The core cluster identifies along with the outliers who do not belong to any meaningful category. Once the core topic clusters are identified, the system further processes outliers, identifying unclassified data points. Outliers are reassigned by k-NN (k-Nearest Neighbors) for saving them in the most relevant topics. Finally, the topic distributions are shown in 3D using UMAP, which provides an intuitive understanding of the clustered data.

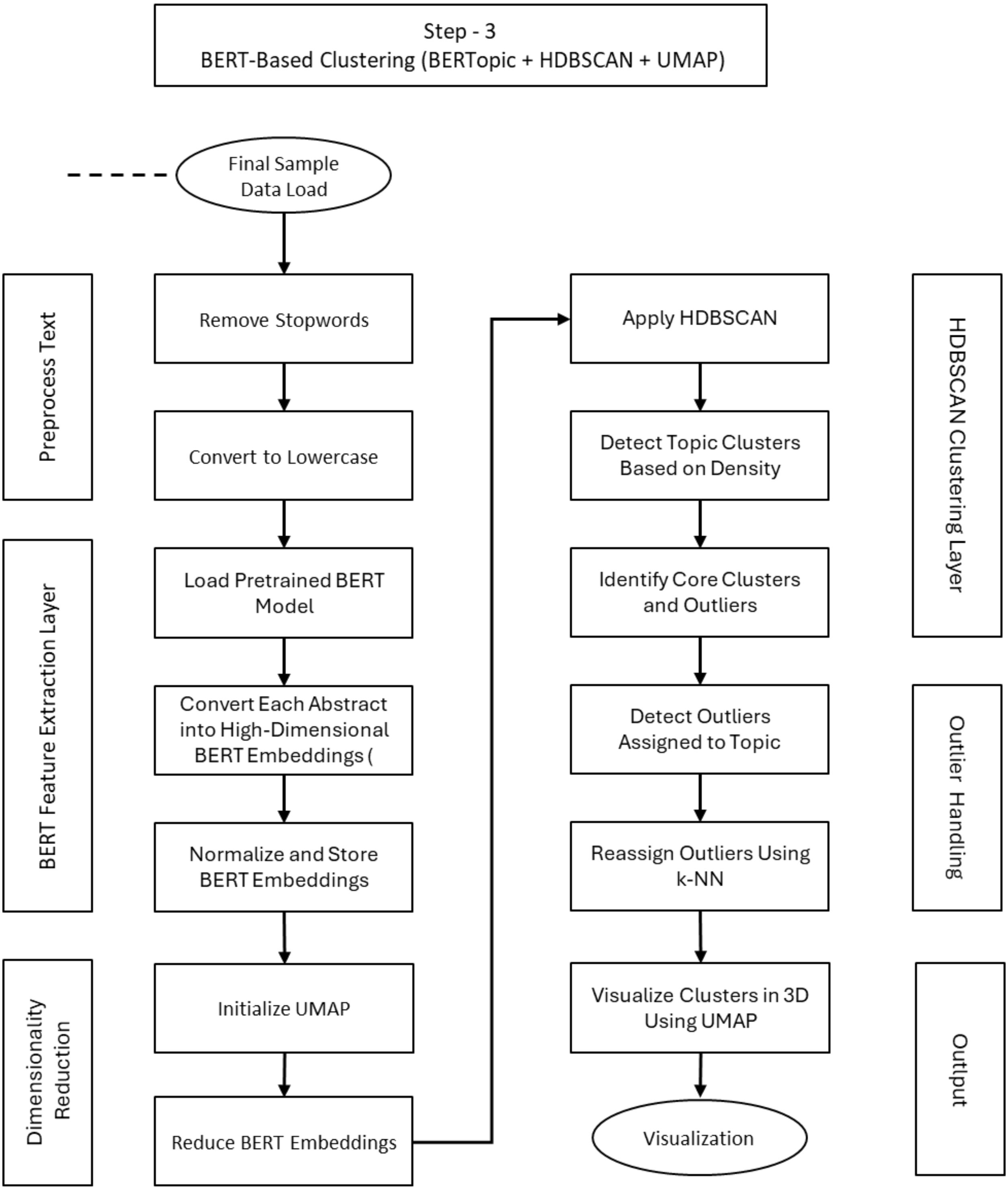

Figure 3. BERT based clustering.

2.4 Dynamic Topic Modeling

Dynamic Topic Modeling (DTM) is an extension of traditional topic modeling that analyzes how topics evolve over time. Latent Dirichlet Allocation (LDA) determines latent topics in the text, taking documents and terms with co-occurrences and placing them into different groups. The dynamic modeling enables the evolution of the clusters to represent the emerging research trends (Blei, 2012; Rabetino et al., 2021).

In figure 4, it has been seen that data was loaded from stage 1 at the beginning. After that cleaning and formatting the texts were performed which includes eliminating stopwords to remove common words and tokenization to break sentences into individual words. Lemmatization was used to reduce words to their base forms. These preprocessing steps ensure that the text is structured properly for further analysis. Once the text is processed, count vectorization is applied to convert the text into a numerical format. Latent Dirichlet Allocation (LDA) is used as part of Dynamic Topic Modeling (DTM) to find underlying topics in the dataset for topic modeling. This includes studying per topic word distributions to see how words are used in different topics.

Topics evolve in time while we track the changes in the content distribution based on the latent semantic themes. Finally, content analysis and visualization benefit us by giving a glimpse of how topics evolve over time and how they are structured.

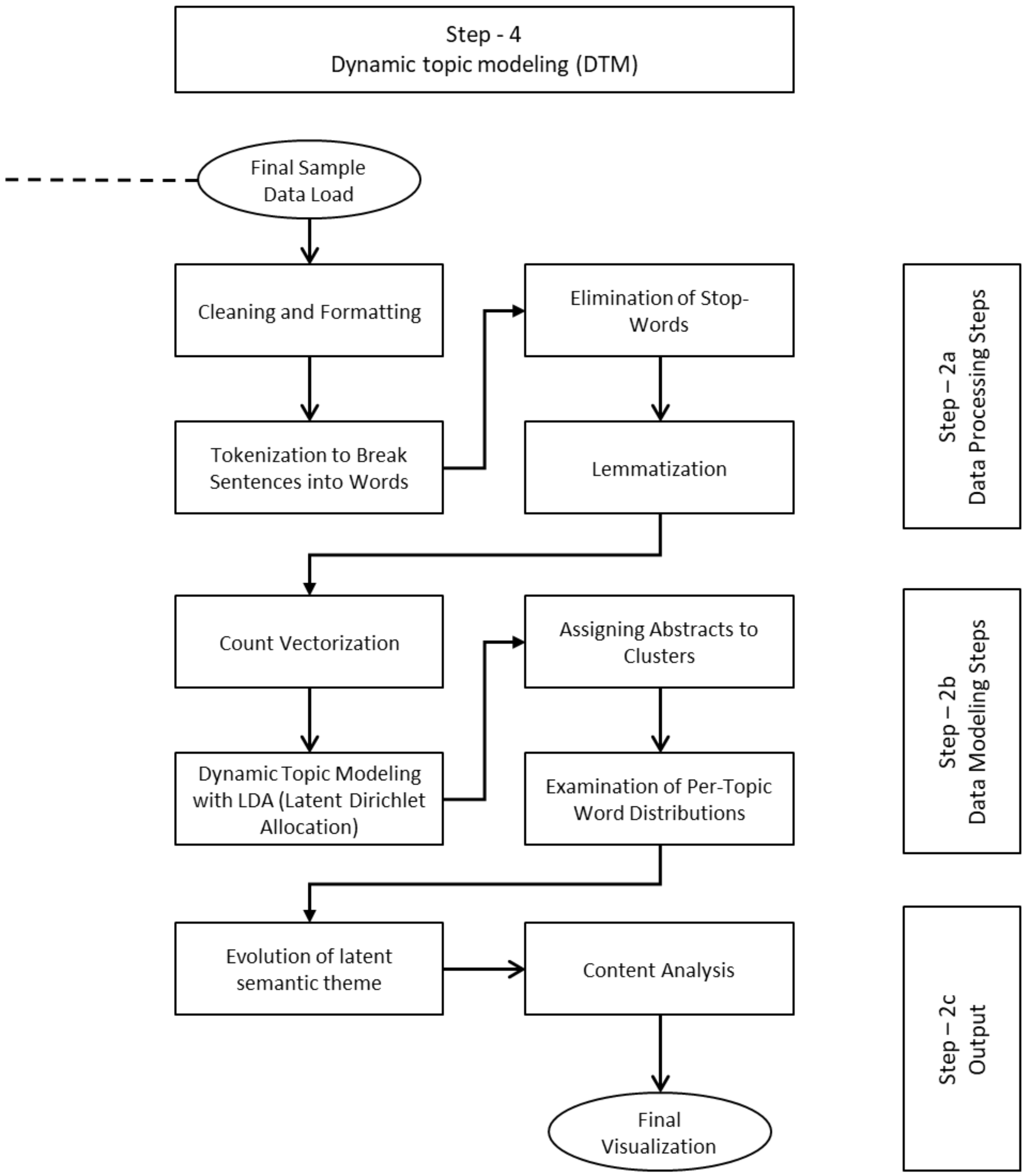

Figure 4. Dynamic topic modeling flowchart.

2.5 VOSviewer Cooccurrence Mapping

VOSviwer is a powerful tool to create clusters of articles. This tool has been used to know the exact cluster of the Scopus articles. Because if we only rely on coding there might be a little possibility of error while making the clusters. So, we have taken the confirmation of the clusters of this software. VOSviewer was used to generate Density Visualization based on co-occurrence analysis of keywords. A threshold of 5 was set which means that only keywords appearing at least five times were included in the visualization. The network map demonstrated in figure 9 was generated in VOSviewer to illustrate keyword relationships. Figure 5 demonstrates the flow diagram of the VOSviewer cluster techniques.

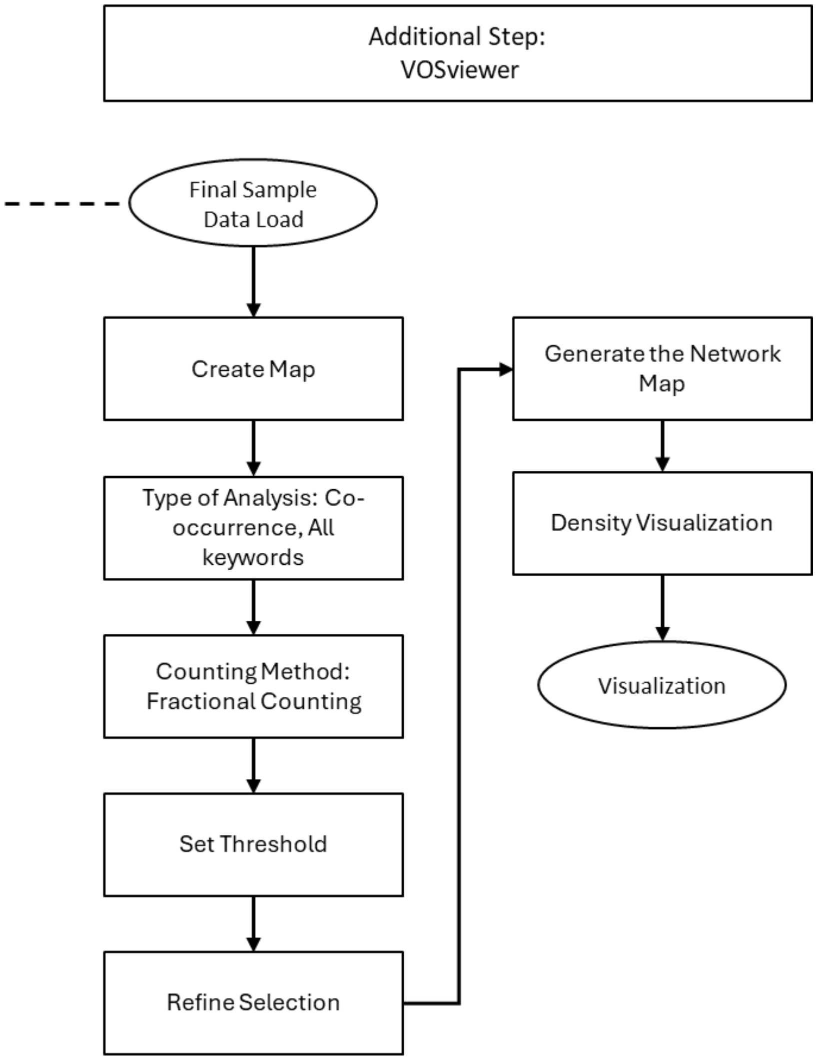

Figure 5. Flowchart of VOSviewer Cooccurrence Mapping.

3. Clustering Visualization

The preprocessing steps for such analysis were done for servitization field data before the modeling phase of the analysis. A standard textual preprocessing was applied to the full text of selected abstracts (Liu, 2019) and the full text was prepared initially. The forming part of these were cleaning and formatting tasks which involved eliminating punctuation, numbers, and words of length less than three, and converting all the text into lowercase. We then tokenized the text to break it into separate words; stop words were removed to remove stop words that were not relevant to our analysis. Only nouns, verbs, adjectives, and adverbs were retained in dimensionality reduction while retaining interpretive power (Blei & Lafferty, 2009). Following that we employed Lemmatization that bring the term to the stem, in other words replaced same meaning different words (Kowsher et al., 2020). This step reduces the size, and the time to analyze data, which is an important factor in success for topic modeling and clustering essential for topic modeling (Chakrabarty et al., 2019).

After this initial preprocessing, we used a list of clusters, each of them linked to a set of keywords related to thematic areas of servitization. Keywords that were relevant to the abstract were assigned to each of these clusters, and each abstract was allocated to one of them. In this section the visualization of these clusters using different clusters will be demonstrated.

3.1 TF-IDF and t-SNE Based Clustering Analysis

TF-IDF vectorization was used to calculate how much significance each term has in each document in relation to frequency and importance between the whole datasets (Lan, 2022). The overlap and distribution of dots in our abstract cluster 3D cognitive map reveals important relationships, similarity, and distinction between different research topic areas. If dots from different clusters interact when they overlap, they mean the abstracts share some common themes, the methodologies, or keywords. In real-world research, topics are not always distinct. Overlapping clusters show that some studies span multiple themes. New topics emerge at the intersection of two or more existing domains. Overlapping dots can indicate developing trends or transitional research fields.

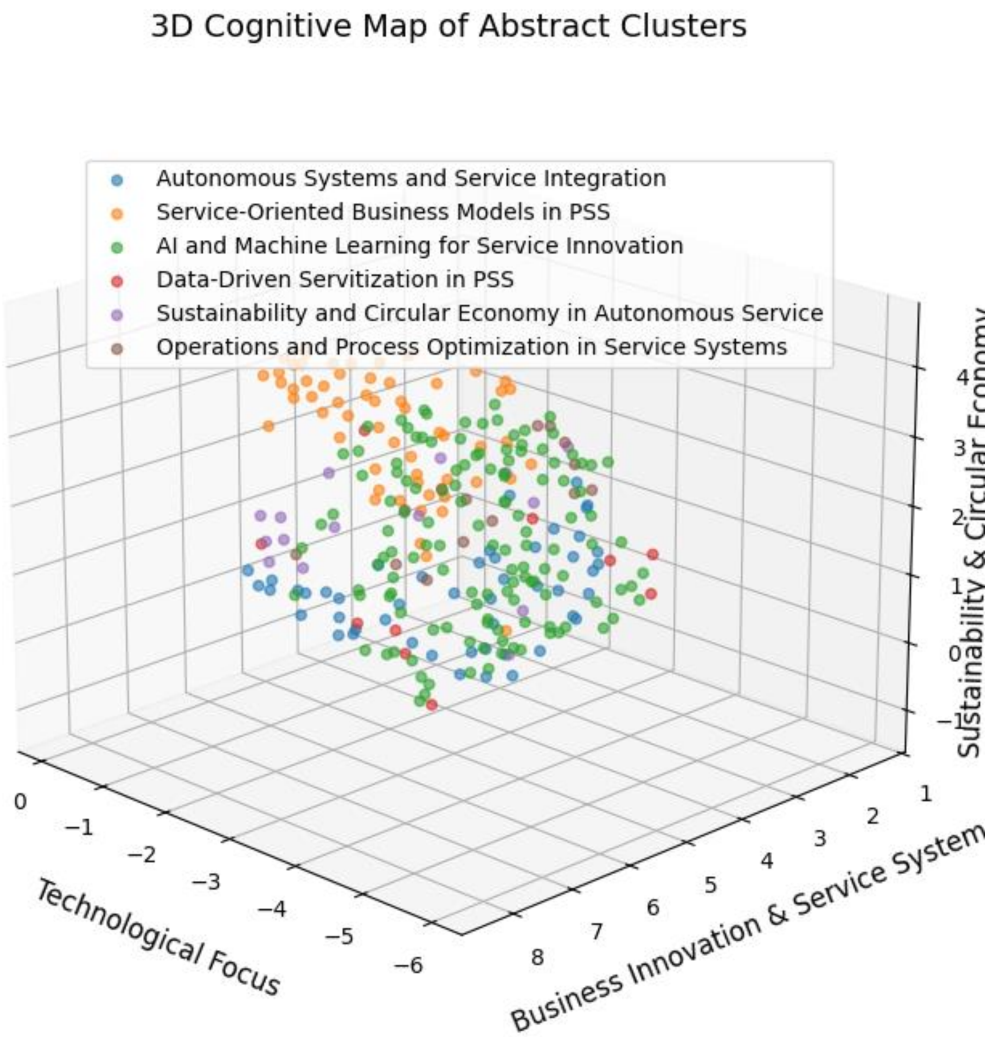

Figure 6. Clustering Visualization using TF IDF.

The X axis represents technological focus because business and service or other circular economy will depend on technology. With the advancement of technology these will revolve around. X axis represents the extent to which a topic or research abstract is focused on technological advancements. Y axis reflects the degree to which an abstract is centered around business models, service integration, and operational frameworks. Z axis captures the level of focus on sustainability and circular economy principles within service and technology research. Technology (X) enables Business Innovation (Y), and both can drive Sustainability (Z).

3.2 BERT-Based Topic Clustering

The 3D scatter plot represents the distribution of research abstracts across three dimensions. Some clusters form in some regions of the 3D space, and the data points are scattered randomly on some other regions. X axis measures the degree of emphasis on AI, automation, and data-driven technologies in the research. Y axis represents how much the research focuses on business models, service strategies, and operational improvements. Z axis demonstrates sustainability, and circular economic principles are integrated into research. Most research topics overlap, and different topics are closer to one or two dimensions, and some are so strongly connected with technology and business or with sustainability.

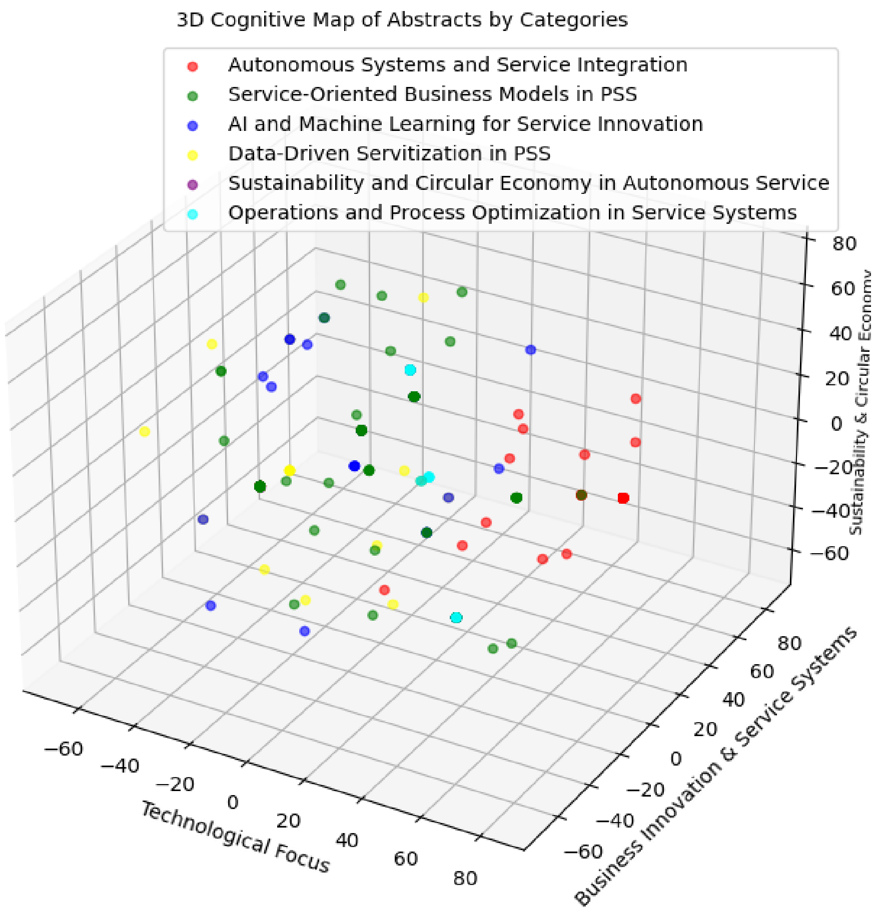

Figure 7. 3D Cluster Visualization using BERT based clustering.

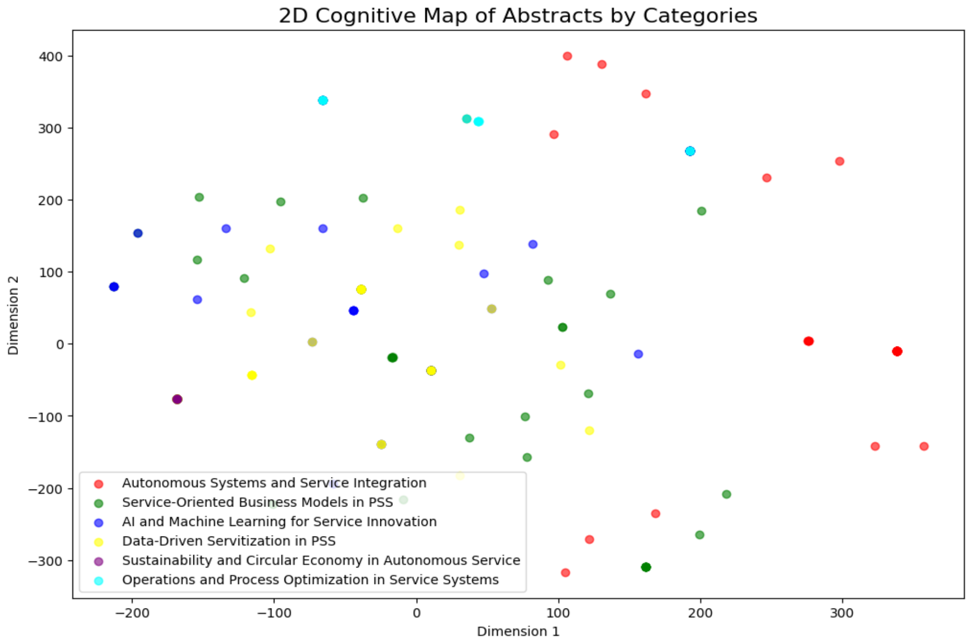

Figure 8. 2D Clustering Visualization.

Research with high technological focus (X) and business innovation (Y) and low sustainability (Z) identifies such areas where there is a lack of sustainability consideration in tech driven service models. High Business Innovation (Y) and Sustainability (Z) but low Technological Focus (X) may indicate business models focusing on sustainability without heavy AI or automation involvement. This 3D cognitive map provides insights into dominant research themes, interdisciplinary overlap, and potential gaps.

In table 1, the axis dependencies and relationships in 3D cognitive mapping of the research clusters have been demonstrated. On x axis, we have used technological focus. Because x axis should be independent, and other axes have dependencies on it. Business innovation, sustainability and circular economy depend on technology because if there is a scope of technological innovation, then we can create market for business and later comes on sustainability. So that is the reason, x axis represents technological innovation. The business innovation should be on y dimension because it is the second major thing in our study. We can even analyse the cluster without the sustainability axis but that would not be much accurate if we consider it.

Table 1. Axis Dependencies and Relationships in 3D Cognitive Mapping of Research Clusters.

Aspect	Technological Focus (X-Axis)	Business Innovation & Service Systems (Y-Axis)	Sustainability & Circular Economy (Z-Axis)
Definition	Emphasis on AI, automation, and data-driven technologies.	Focus on business models, service strategies, and process optimization.	Integration of sustainability, resource efficiency, and circular economy principles.
Dependency	Enables business transformation and service innovation.	Utilizes technology for efficiency and new service models.	Advanced technology can promote or challenge sustainability.
Interconnection	Tech adoption impacts how businesses innovate.	Business transformation depends on emerging tech.	Sustainable solutions are often tech driven.
Typical High Values	AI & Machine Learning, Predictive Analytics, IoT	Service-Oriented Business Models, Process Optimization, Subscription-based Services	Sustainable AI, Circular Economy, Low-Carbon Innovation
Typical Low Values	Theoretical studies with minimal tech applications	Business models without digital transformation	Research lacking environmental/resource impact
Impact on Research Trends	Drives automation, smart services, and efficiency.	Help create innovative service ecosystems.	Encourages eco-friendly and responsible service models.
Challenges & Limitations	Rapid tech evolution may outpace adoption.	Organizational resistance to innovation.	Trade-offs between sustainability and cost-effectiveness.

3.3 VOSviewer Clustering

VOSviewer is used to display the density visualization of keyword co-occurrence. In here, different colors mean clusters of thematically related research areas. The color intensity in figure 9 reflects the frequency and strength of keyword associations. This visualization allows us to find the important themes in the dataset as to what topics are important and how they present with one another. Artificial Intelligence (AI), Machine Learning, Business Models, and Servitization appear as major research areas. The keywords of digitalization, service innovation, and decision support systems denote the convergence of technology, business, and optimization. The co-occurrence of terms suggests areas where different fields interact. For example, AI for service-oriented business models or sustainability in autonomous systems.

The presence of distinct color clusters indicates thematic groupings that align with the six research clusters. Autonomous Systems and Service Integration cluster is indicated by keywords like robotics, automation, intelligent systems. Service-Oriented Business Models cluster is indicated by keywords business models, digital transformation, and servitization. keywords like big data, digital servitization, digital storage make the cluster Data-Driven Servitization. Sustainability and Circular Economy in Autonomous Services cluster is represented by the keywords like sustainability, ecosystems, and sustainable development. Operations and Process Optimization in Service Systems cluster has some keywords like decision making, optimization, process control.

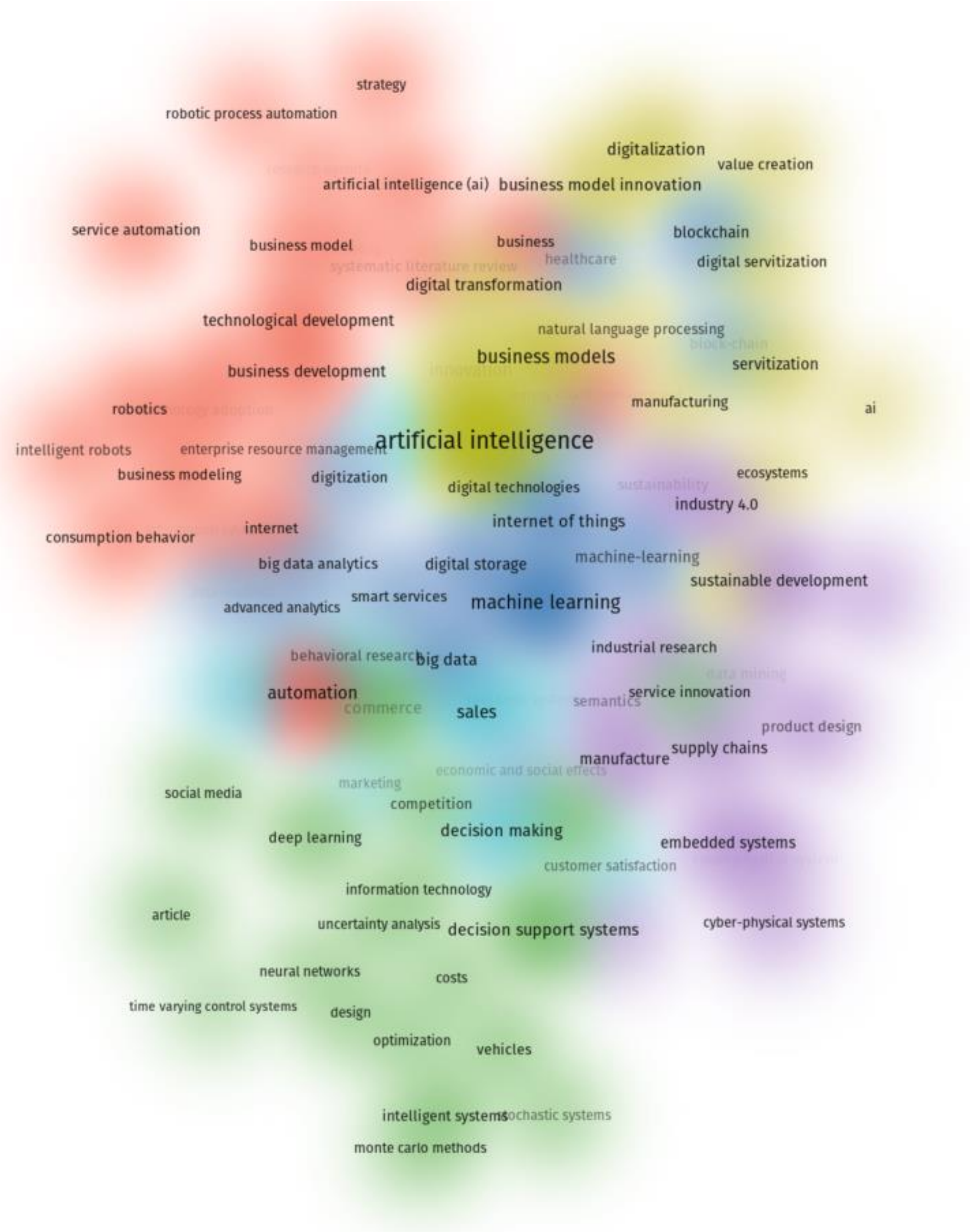

Figure 9. Density Visualization, Threshold: 5 Co-occurrence, All keywords, Fractional counting.

4. Analyzing the Cluster Findings in Servitization Research

Articles in servitization research were categorized using BERT based clustering, based on vocabulary patterns, which showed that there were six emerging research sub streams. Content analysis of foundational articles identify sub stream and indicate a different thematic focus within the field. In the table 2 the research focus and findings have been discussed for the sub streams. These six primary sub streams are:

1. Autonomous Systems and Service Integration
2. Service-Oriented Business Models in Product-Service Systems (PSS)
3. AI and Machine Learning for Service Innovation
4. Data-Driven Servitization in Product-Service Systems (PSS)
5. Sustainability and Circular Economy in Autonomous Service
6. Operations and Process Optimization in Service Systems

The Autonomous Systems and Service Integration cluster has concentration in connecting autonomous technologies, for example, robotics, Internet of Things (IoT) and AI driven automation, in service operation. With autonomous systems, service quality is being strengthened, costs are being reduced, and efficiency is being enhanced. Traditional product-based businesses are now shifting towards the value of deliveries through reporting services and products powered by AI. In Service Oriented Business Models cluster, PSS integration is researched that helps the businesses generate new revenue streams and strengthen relationships with customers. The delivery of services, optimization, and improvement of services are being revolutionized by AI and ML. The AI and Machine Learning for Service Innovation cluster explores how AI can be used to improve service innovation through automation, predictive analytics, and intelligent decision making. The Data-Driven Servitization cluster studies the applicability of utilizing big data, analytics and AI in creating metropolitan servitization strategies in Product-Service Systems (PSS). Companies are using real time data to make their service more personal, improve their operation, and create new businesses. The integration of autonomous technologies with sustainable business practices is becoming important day by day. This cluster explores how AI and automation contribute to resource efficiency, waste reduction, and environmentally friendly service models. Operations and Process Optimization in Service Systems cluster shows how AI-driven process automation improves service delivery and business performance. We can see that AI and automation are transforming the service operations by optimizing the workflows in a specific operation and then it reduces the inefficiencies, and by improving decision-making.

Table 2. Research focus and findings from the defined servitization clusters.

Clusters	Research Focus	Findings
Autonomous Systems and Service Integration	In this area, there is lots of innovation potential for autonomous maintenance services, self-driving vehicles as service offerings, and AI optimized product service processes. Moreover, they are not only transforming the classical PSS models however, but also integrating more and more advanced technologies that add to the efficiency and customization of the versions of service delivery (Naeem et al., 2024; Sjödin et al., 2023). Batalden et al., (2017) talks about how autonomous technology can be used for making ships and offshore work better (Batalden et al., 2017; Sandvik et al., 2024). New performance measures for autonomous shipping, showing trade-offs between cost, environmental benefits, and safety compared to traditional transport in different research (Zis et al., 2023). Leminen et al., (2022) categorizes four types of autonomous vehicle solutions and links them to digital servitization models, emphasizing business model flexibility and value creation	Fargnoli et al. (2019) showed the significant contribution of modular design methodologies in integrating autonomous systems into PSS, particularly emphasizing the customer driven approach, minimizing design conflicts and over engineering (Fargnoli et al., 2019). Autonomous vehicle (AV) transit-oriented systems development provides for integration of AV with public transport to improve first mile connections and minimize fleet sizes to improve service efficiency (Wen et al., 2018). Research should explore how smart ships can improve safety, economy, and the environment by using better routes and more cargo space. It also looks at challenges like old rules, data management, and new tech for self-sailing ships (Batalden et al., 2017; Sandvik et al., 2024). The study examines autonomous shipping and vehicle solutions, introducing a KPI framework aligned with EU sustainability goals while exploring digital servitization business models that enhance value creation, adaptability, and efficiency in emerging industries (Leminen et al., 2022; Zis et al., 2023).

	over just technology (Leminen et al., 2022).	
Service-Oriented Business Models in PSS	This cluster focuses on building new service-oriented business models based on the use of autonomous systems to provide better customer value. Research topics include subscription-based services for autonomous products, outcome-based contracts with respect to autonomous technologies and integrations of sustainability metrics in business models that depend on automation. Some research examines how Servitization and Industry 4.0 connect through business model innovation, proposing a framework with nine service configurations and case studies to show their impact on value creation (Frank et al., 2019). LISA is an service event-driven architecture for data integration which can create flexibility for the Future manufacturing systems (Theorin et al., 2017). Additionally, A novel Context-Product-Service data model was introduced (Z. Wang et al., 2021). E-commerce business model called Cloud Laundry	In PSS, business models are developed around product oriented and use oriented perspectives, which rely on the contracts, marketing and network collaborations to get the jobs accomplished effectively and in consistency with long term customer relationships and sustainability (Reim et al., 2015). As the last step, a structured PSS board to visualize the processes helps companies to be effective in bringing in the products and services to meet customer requirements. Frank et al., (2019) identified nine service configurations, highlighting dual value creation, and emphasizing trust, data security, and digital integration challenges (Frank et al., 2019). Big Data and virtualization in manufacturing cyber-physical systems is essential while addressing cybersecurity risks (Babiceanu & Seker, 2016; Lehrer et al., 2018). IoT-enabled SHIP enhances physical asset and service sharing efficiency (Qiu et al., 2015). High reliability in requirement extraction was achieved using IoT and other context service (Theorin et al., 2017; Z. Wang et al., 2021).
	AI and machine learning plays an important role in autonomous systems, to enhance service efficiency by applying automated predictive analytics and improving customer interaction (Kohtamäki, Brekke, et al., 2024). Key research focus is on autonomous operations machine learning algorithms, AI driven predictive maintenance,	PSS uses AI and machine learning to provide data analysis for predictive and decision support models in models which are tailored customer services and predictive maintenance solutions (Qu et al., 2016). Integration of AI with cyber physical systems helps life cycles of the product be optimized in order to improve operational efficiency as well

	and intelligent automation in PSS offerings.	as customer satisfaction (Maleki et al., 2018).
AI and Machine Learning for Service Innovation	The intersection of artificial intelligence (AI) and business model innovation (BMI) need to be explored which highlight the critical role of top management (TM) in facilitating AI-enabled BMI (Jorzik et al., 2024; P. Wang & Swanson, 2007). It has been also known that four types of digital transformation journeys, detailing the roles of top, middle, and frontline managers in both evolutionary and transformative migrations (Burström et al., 2021; Volberda et al., 2021). It has to be emphasized the importance of advancing AI capabilities for internal process optimization and social innovation services to achieve effective servitization (Abou-Foul et al., 2023; Bahoo et al., 2023).	Professional Services Automation (PSA) is important in launching IT innovations, specifically through mobilization and legitimation activities (P. Wang & Swanson, 2007). Most of the research identifies the dynamic relationships between technology, business models (BM) (Fritschy & Spinler, 2019; Yun et al., 2016). Manufacturing firms need three key AI capabilities which include efficient data management, algorithm development, and broad AI accessibility within the organization. These capabilities are interdependent and require significant investment to develop appropriate routines and infrastructure (Sjödin et al., 2021).
Data-Driven Servitization in PSS	Data analytics plays a great role in autonomous systems in PSS. It discusses the usage of big data in service customization (Saura et al., 2024), automated by IoT and real time insights boosting autonomous decision making in the service ecosystems (Lechner & Reimann, 2020). Study demonstrated by Chiu & Chuang (2021) that the smart chatbot system significantly reduced the number of questions required to generate recommendations, improving user experience and operational efficiency (Chiu & Chuang, 2021).	Big data and analytics are core of servitization, via data driven approaches such as through advanced analytics and smart services which adapt to users' behaviors and requirements (Maisenbacher et al., 2014). The integration of sensor in PSS designs enables real time monitoring and adaptive treatment enabling personalized user experiences and predictive maintenance possibilities (Aurich et al., 2008). Saura et al. (2024) suggest that adopting data monitoring and analysis strategies is crucial for optimizing operations and enhancing decision-making in the industry. The

	Some of the research findings indicate that meta-organizations effectively support technology-based entrepreneurs in creating new business opportunities through data-driven innovations (Battisti et al., 2022).	study by Ghosh et al (2023) emphasizes the importance of consumer reviews and ratings as critical indicators for businesses in the refurbished market, aiding in understanding consumer behavior and enhancing sales strategies (Ghosh et al., 2023).
Sustainability and Circular Economy in Autonomous Service	Circular economic principles need to be applied within autonomous solutions to create sustainable service models. In this field we need topics like autonomous recycling systems, resource optimization in autonomous factories and energy efficient autonomous logistics (Kohtamäki et al., 2022). The integration of Circular Economy principles in the automotive manufacturing sector is promoting recycling and sustainability practices (Jerry A. Madrid, 2023). The linkage of sustainability and technological innovation in this research area focuses on how autonomous systems can help reduce waste, promote material reuse, and coordinate more efficient resource management (Kohtamäki, Bhandari, et al., 2024; Rabetino et al., 2024).	PSS models oriented towards sustainability are concerned with resource efficiency and waste reduction and embedded in systems design to achieve maximum eco efficiency of products and services across their entire lifecycles (T. S. Baines et al., 2007). PSS design methodologies which embed circular economy principles directly into environmental goals within PSS operations and planning (Geng et al., 2010). Also, artificial intelligence (AI) is reshaping value co-creation in B2B industrial markets (Leone et al., 2021). Lee et al. (2012) propose a dynamic and multidimensional approach to measure product-service system (PSS) sustainability, integrating system dynamics (SD) and triple bottom line (TBL) methodologies.(Lee et al., 2012). Teles et al. (2018) finds out that both electric car-sharing projects, VAMO and EMOTIVE, contribute positively to sustainability (Teles et al., 2018).
	Reduction of service delivery costs, improvement in accuracy and real time adjustments can only be achieved through process optimization through autonomous systems (Pieroni et al., 2019). Areas of research include autonomous systems for timely monitoring service; automated control for service	Integrated design processes to effectively process design and manage processes to optimized resource allocation and customer satisfaction by adapting to demand (Hamzah & Ismail, 2020). Simulation based approaches for capacity planning and service optimization lead to practical insight

Operations Process Optimization in Service Systems	delivery with optimization algorithms for continuous improvements in service operations (Demirkan & Delen, 2013). Chae (2014) visualizes that IT-Enabled Services (IES) and IES innovation through the lens of complexity theory for nonlinear interactions in optimization process (Chae, 2014). Tung et al. (2014) analyzed that simple service machine (SSM) and intelligent service machine (ISM) can facilitate systematic service significantly (Tung et al., 2014).	on dealing with uncertainty of delivery and inventory control problems for the industry applications (Toyouchi et al., 2001). Robotic Process Automation (RPA) can enhance financial processes for the operation of medium-sized companies and large corporations (Lacity et al., 2021; Syed et al., 2020; Willcocks et al., 2017). Also, multi-agent e-services method significantly reduces customer complaints related to telecom services by improving the management of user requests and legacy systems (Chou & Seng, 2009).

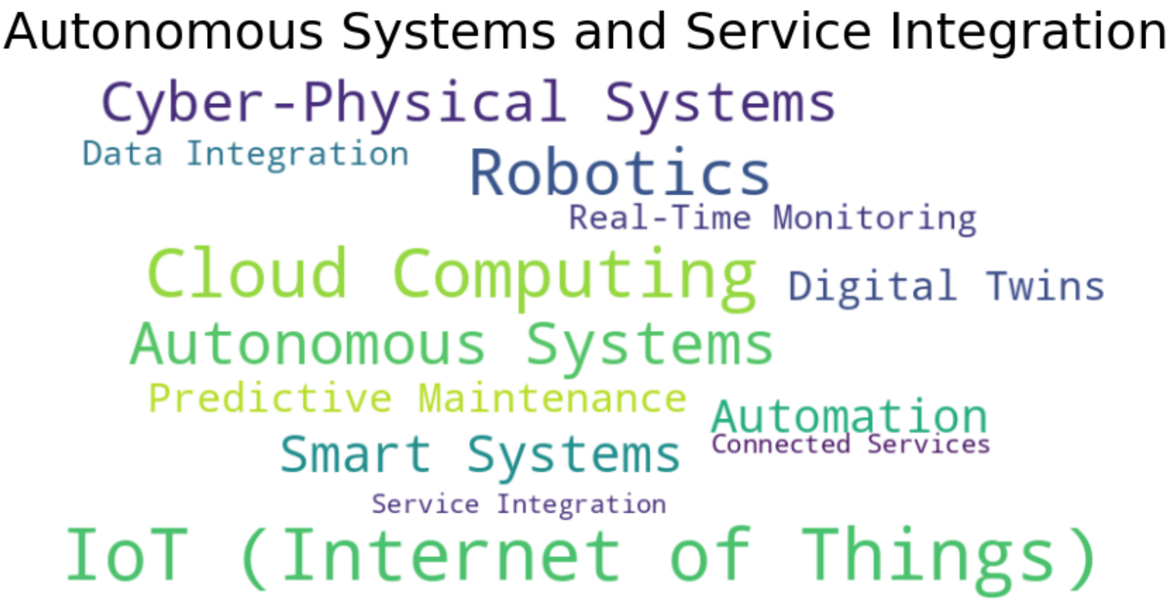

Figure 10. Visualization of keywords in Autonomous Systems and Service Integration.

Figure 11. Visualization of keywords in Service-Oriented Business Models in Product-Service Systems (PSS).

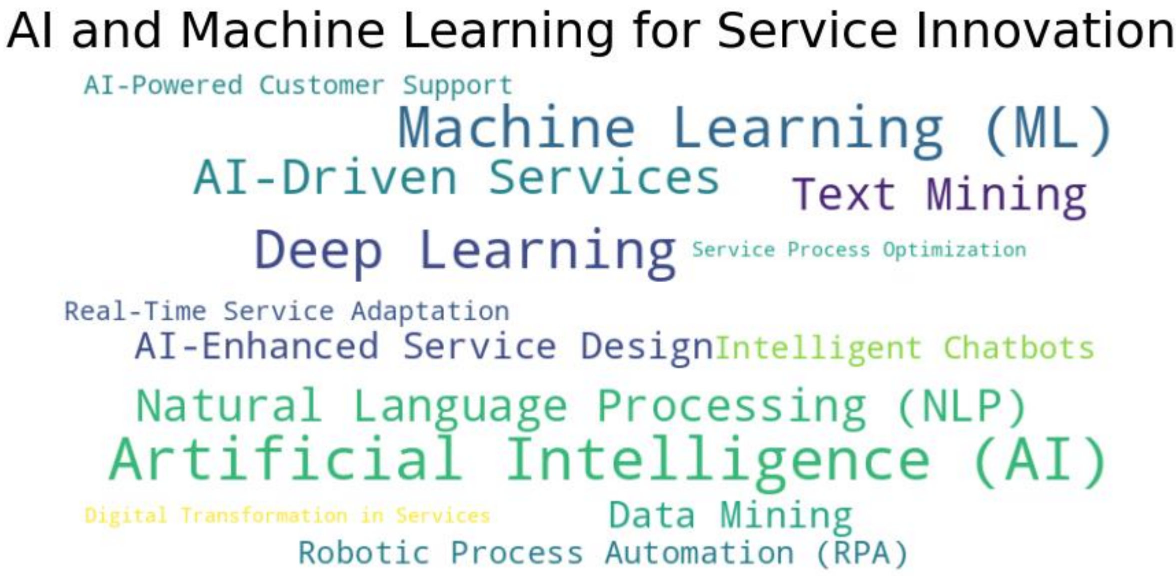

Figure 12. Visualization of keywords in AI and Machine Learning for Service Innovation.

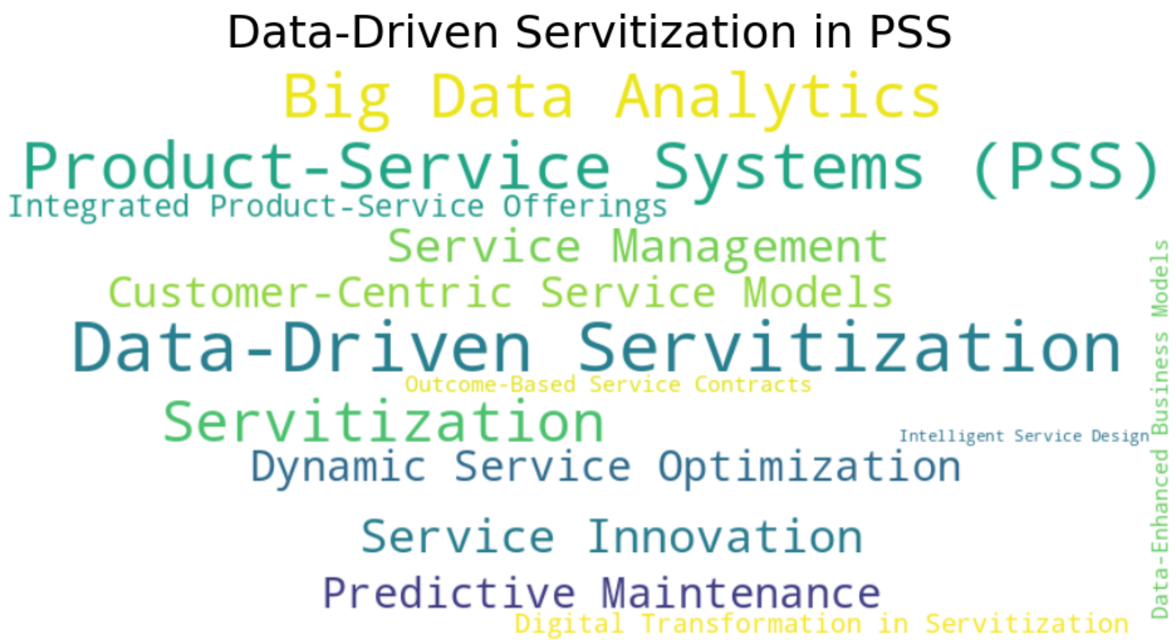

Figure 13. Visualization of keywords in Data-Driven Servitization in Product-Service Systems (PSS).

Figure 14. Visualization of keywords in Operations and Process Optimization in Service Systems.

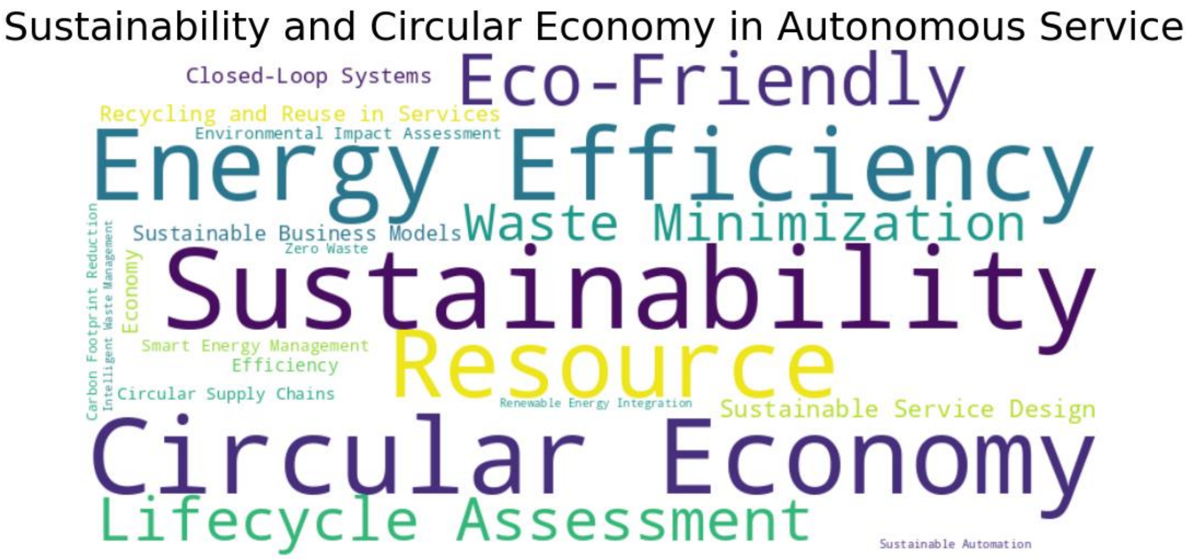

Figure 15. Visualization of keywords in Sustainability and Circular Economy in Autonomous Service.

The six research clusters show how different methods are being used to study AI-driven servitization and service optimization. From figure 16, we can see different methodologies over different clusters. Autonomous Systems and Service Integration relies heavily on Machine Learning (40%), along with qualitative research (15%), case studies (12%), and literature reviews (10%). This suggests a strong focus on automation and AI's role in improving service systems. Service-Oriented Business Models in PSS is mainly based on framework-based research (30.8%), followed by reviews (23.1%), analytical methods (15.4%), and qualitative studies (13.4%), indicating a structured approach to understanding new business models.

AI and Machine Learning for Service Innovation is mostly explored through case studies (40%), with qualitative research (22%), exploratory studies (18%), and surveys (5%), showing that real-world applications of AI are a key focus. Data-Driven Servitization in PSS highlights the importance of systematic literature reviews (22.8%), sentiment analysis (20%), and framework-based approaches (14.3%), reflecting the growing role of data analytics in improving service offerings.

Sustainability and Circular Economy in Autonomous Service is mostly studied through simulation methods (36.7%), alongside qualitative research (25%), other methods (33.3%), and case studies (8.3%), showing a mix of modeling and real-world analysis to understand sustainability efforts. Lastly, Operations and Process Optimization in Service Systems include systematic literature reviews (13.3%), case studies (13.3%), and design science research (11.3%), with other approaches (20%), emphasizing a blend of different methods to improve efficiency in service operations.

This study will guide further research to know about the current methodologies which are mainly used for analysis. It is important because the existing methodologies may have different flaws, and we need to explore other methodologies and techniques to get a better understanding of autonomous servitization.

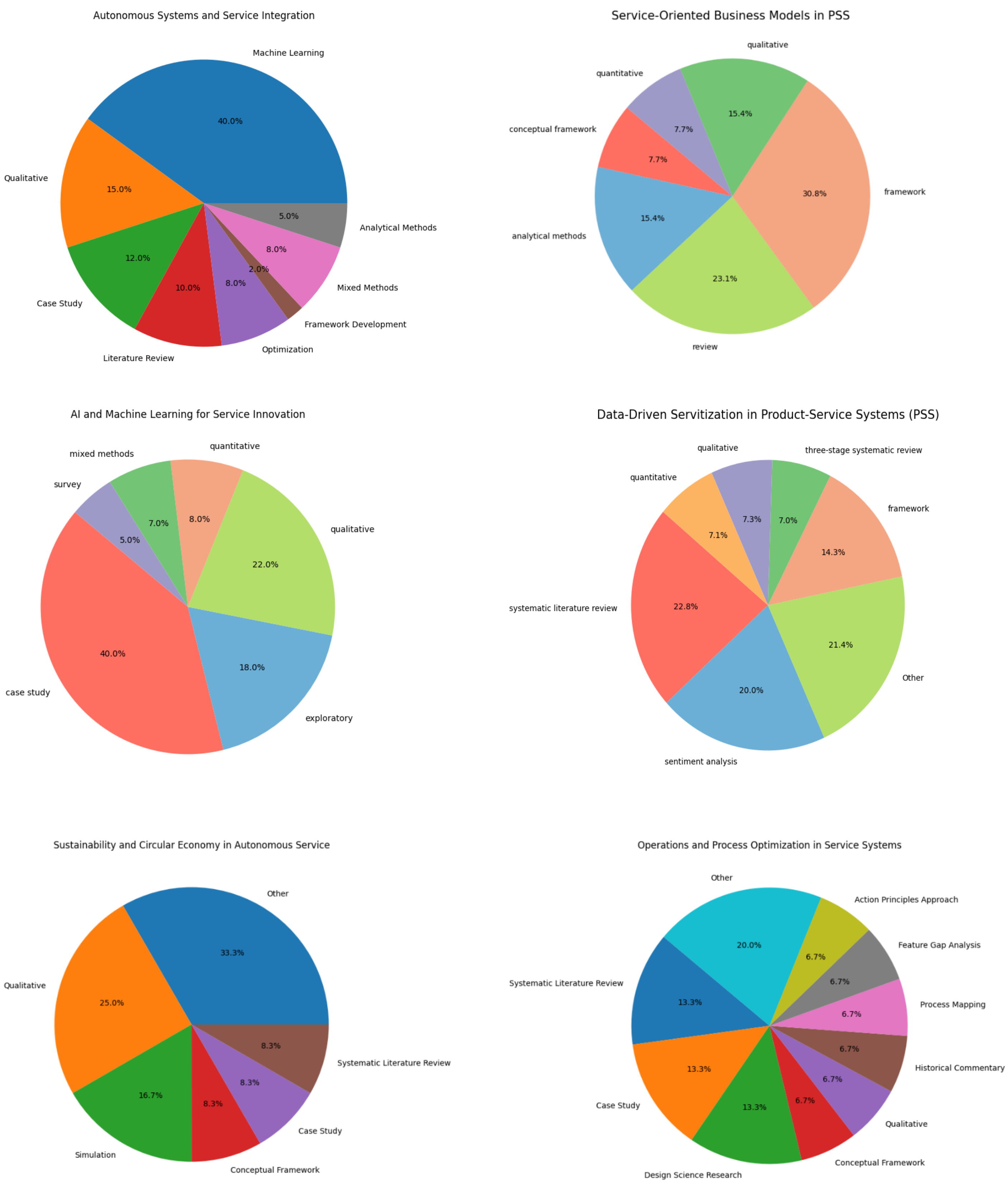

Figure 16. Pie chart of methodology percentage over different clusters.

5. Convergence of Servitization and Autonomous Solutions in Service Systems

Dynamic topic modeling (DTM) is a method where the vocabulary of a research domain is made based on the proximities of the vocabulary and the topics within a domain and then we track changes to this relationship over time. Following that, this analysis assumes that academic vocabulary and narratives continually evolve as each shapes the other according to disciplinary norms. These emerging patterns are the formations of multiple distinct sub streams within the overall research domain and are a meta narrative that constituted the flow of the field. If we read these sub streams, we can notice that a particular ‘theme’ or topic rises and falls along the collective output. This study analyzes each sub-stream theme over a particular period to identify fluctuations in prominence and influence within this theme.

We observe patterns and perspectives within the research articles for each latent topic and discuss the narrative elements (strategy, structure and performance) shaping the discussion. The coalescence of this narrative is of the evolving nature of academic vocabulary. There is vocabulary that converge, leading to a united language spread across sub streams and vocabulary that diverge based on disciplinary influences. We find six main clusters in this domain, each one corresponding to unique vocabularies, trajectories, and thematic focus over time.

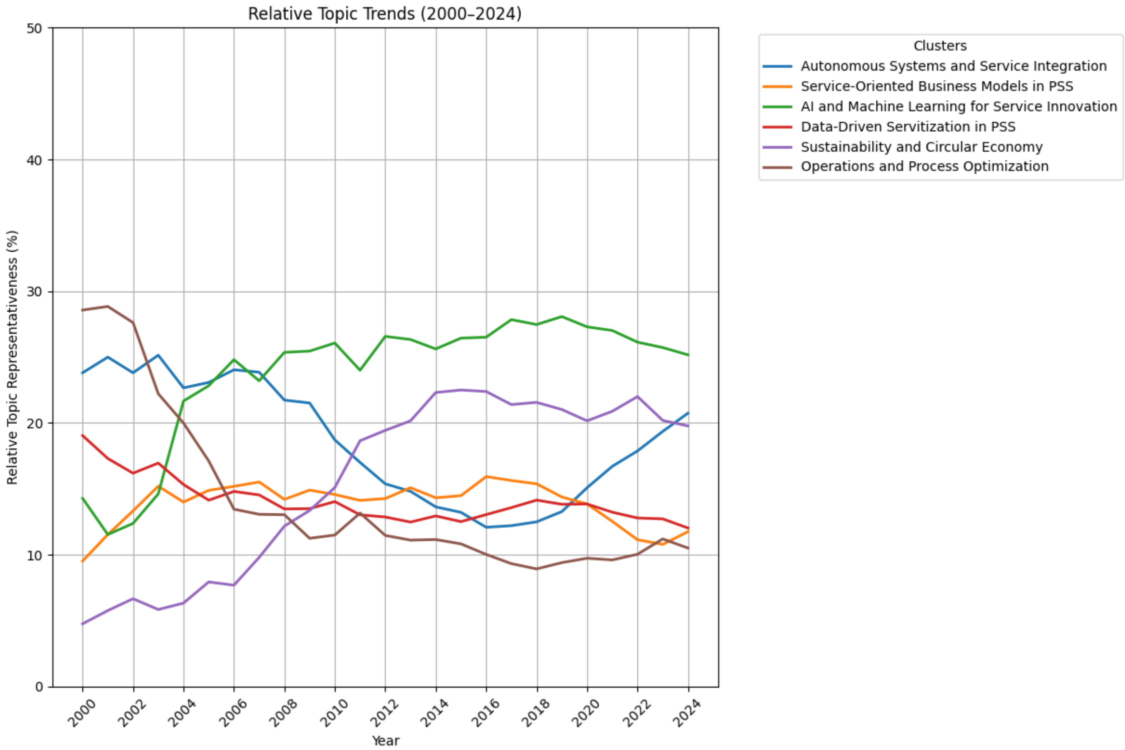

Figure 17. Thematic revolution.

This AI and ML service innovation cluster has ‘hot’ trend, increasing publicity since 2000s. This rising tenor about AI & ML speaks to the significant role AI and ML must play in transforming service industries from automation to personalization and decision making. This area in the early days used to have a perspective on predictive analytics and customer interaction models which then had an exponential growth from 2005 to 2015. The foundational work focused on how to use data to improve customer service, optimize service operations, and enable intelligent decision-making processes.

Over the past few years, there has been a lot of diversity in AI and ML in service innovation, with research spreading to natural language processing, deep learning and recommendation systems. The integration of AI in service-oriented applications leads to this thematic diversification and a sustained upward trend. This trajectory of service sector advancement through AI/ML suggests that AI/ML will continue to move from a market niche to a stable and fundamental driver of service innovation. (Jordan & Mitchell, 2015).

The Autonomous Systems and Service Integration cluster was first on the rise in 2000s, going up rapidly and reaching its peak in 2010 along with the interest in automation and robotics. While demand for increased efficiency within complex service environment has pervaded early vocabulary in this field, it has typically focused on system autonomy, robotic integration and intelligent control (Siciliano & Khatib, 2008). After 2010 the representatives of this theme became stabilized, showing the maturity stage where autonomous systems became standardized in the service application. From 2016 onward, the trend reversed as autonomous systems began to converge with AI, cloud computing, and data-driven service platforms. At this optimization stage rather than the breakthrough innovation stage, we are in the current “warming” trend. Now the research concentrates on resilience and scalability, improving reliability of these systems across various industries (Kowalkowski et al., 2017).

The Service-Oriented Business Models in PSS cluster evolved from early 2000 to around 2015 showcasing that most business strategies are moving towards service delivery. This period marked an increase in the use of terms including value co-creation, servitization, and customer-centric business models built mainly on works on servitization (T. S. Baines et al., 2007). This theme then stabilized as the vocabulary became well established in the service-oriented business literature after 2015. This is a trend toward an evergreen topic, meaning that the theme is still relevant but not much changed, which means the field is now focusing to fine tune and adapt existing models to new market realities as opposed to embracing a new worldview from scratch. (Oliva & Kallenberg, 2003).

Data Driven Servitization is on the rise as a ‘warming’ trend, as data is changing the product-centric business model to a service model. This theme has grown consistently from about 2010 as businesses started to use data analytics to learn about product usage, maintenance and customer behavior. In this cluster, early vocabulary focuses on terms such as predictive maintenance and customer analytics, preparing children to think in data terms to lead data driven service innovation. The vocabulary expanded to more advanced analytics, including machine learning models and real time data integration, at a stage near 2020, giving data driven servitization an advanced stage. The fact that there is ongoing growth suggests that data analytics will be important for improving the service-based business models operating in product service systems (Opresnik & Taisch, 2015).

The cluster Sustainability and Circular Economy expresses a growing emphasis on resource efficiency and environmental responsibility. The trend toward sustainability on a global level has corresponded with gradual but steady growth of this theme since about 2015. Early vocabulary centered on re-source optimization and waste reduction and foundational studies that called for sustainable practices in service systems (Geissdoerfer et al., 2017). Vocabulary from more recent times includes terms like circular economy models and sustainable autonomous systems, integrating the term sustainability into autonomous technologies. This 'warming' trend is a future oriented research area where sustainable service innovation becomes increasingly important for environmental and economic reasons (Bocken et al., 2016).

The rapid rise in the early 2000s for the Operations and Process Optimization cluster is evidence of the demand for Service Systems to become more efficient. This cluster is related to applying operational research methodologies (such as lean management, process re-engineering) in a way to optimize the delivery of service. The language of this theme peaked around 2010 marking a 'cold' trend in which the vocabulary leveled off in an already well integrated field within a service management literature (Mathieu, 2001). The field stabilized since 2010, and while process optimization will continue to advance, no longer quickly, it is no longer a fast-developing research area. Under these conditions, the vocabulary continues to include core concepts, such as efficiency and resource allocation, demonstrating that this area is fundamental, but not at the frontier for service research innovation.

Table 3. Trends of the themes and alignment with TRL.

Cluster	Main Theme	Trend	TRL Alignment
AI and Machine Learning for Service Innovation	Leveraging AI for predictive service insights and automation	**Hot:** Strong upward trend, continuously rising	High readiness, applied and commercially relevant
Autonomous Systems and Service Integration	Developing autonomous technologies for integration in services	**Warming:** Continuous growth as AI is growing over everything and gain importance	Even spread across TRLs, foundational and applied research
Service-Oriented Business Models in PSS	Shifting from product-centric to service-oriented business models	**Evergreen:** Stabilizes post-peak, remains relevant in mature applications	Mid-to-high TRL, mature applications
Data-Driven Servitization in PSS	Integrating data analytics into service models	**Warming:** Moderate upward trend, moving towards optimization and established practices	Balanced TRL, foundational and applied research
Sustainability and Circular Economy in Autonomous Service	Incorporating sustainability practices in autonomous service design	**Warming:** Continuous growth as environmental considerations gain importance	Early to mid TRL, emerging relevance
Operations and Process Optimization in Service Systems	Optimizing operational processes for service efficiency	**Cold:** Slight decline post-peak, indicating foundational but less dynamic	High mid-TRL, foundational methodologies

6. Technological Maturity and Adoption Levels

The levels of Technology Maturity and Adoption are represented by so-called Technology Readiness Levels, or briefly TRLs—play an important role for practical application potential assessment and subsequently for the development path that specific research clusters will have to undergo. Clustering analyses through TRLs allow drawing very valuable insights on which technologies are ready for market introduction, where research is needed, and in which fields investment will be promising to engage.

According to Hasanah et al. (2020), TRLs have a place in the substantial assurance of technology readiness for the commercial phases. Their study on the products of aromatherapy shows that assessing TRL helps to validate innovation readiness and reduces the failure rate in market implementation systematically based on performance criteria and metrics. (Hasanah et al., 2020). Miller et al. (2016) extend the TRL frameworks to include aspects of human and system readiness and identify how TRL evaluations underpin complex system integration decision-making. Their research work indeed digs out how TRLs, together with System Readiness Levels (SRL), can assess technologies for maturity and integration readiness, thus providing essential information to investment and strategic planning (Miller et al., 2016).

Blichfeldt and Faullant (2021) indicate how firms with high TRLs of digital technologies gain more radical innovations and, therefore, a competitive advantage. Their European manufacturing study shows that the TRLs can predict not only innovation but also market success (Blichfeldt & Faullant, 2021). Again, in PSS, technology adoption considers organizational and customer readiness. Technology Readiness Index (TRI) reference measure the degree of comfort that users have with technology-based services (Parasuraman, 2000). This aspect is crucial for clusters such as "Autonomous Systems and Service Integration," where the step in technological capability needs to be supplemented with growth in customer readiness (El-Gohary & Eid, 2013).

Organizational readiness is critical for successful adoption, especially in clusters depending on complex service systems. In digital innovation, an organization must be ready on many dimensions, including resource readiness, cultural alignment, and partnership readiness, among others, for effective implementation. This kind of approach can also be given to a cluster such as "Operations and Process Optimization in Service Systems," where commitment by an organization has to match up with technological maturity for best results (Lokuge et al., 2019).

Moreover, technological readiness models have been adapted across industries, including the field of animal health, indicating therefore the broad range of applicability for frameworks on technological readiness. The TRL model for vaccine and drug development in animal health, for instance, they illustrate how TRL can be tailored to suit the needs of a given industry from early research into basic development to life-cycle management. Similarly, even for clusters in AI and Machine Learning for service innovation, too, TRL may offer a well-structured path of translating technologies from research into real-world applications. (Arnouts et al., 2022).

According to Langley (2022) the research in Data Driven Servitization is mainly carried out at TRL 1-3 where newly developed frameworks, and some early applications are defined. The transition to "Digital Servitization" will enable conventional business to turn itself into service-oriented models (Kohtamäki et al., 2019), focuses on data analytics, and Industry 4.0 technologies (Rajala et al., 2019). However, the slower rate of adoption of those frameworks in practice would indicate a disconnect between research and real-world applications. Research will need to be focused on overcoming data management challenges and operationalizing insights within PSS frameworks if the sector is to advance along higher TRLs (Arioli et al., 2022; Langley, 2022).

The research areas of Autonomous Systems and Service Integration generally focus on early to midterm development levels, TRL 1-3, and research the basic enabling technology needed in realizing the integration of autonomous systems into services

(Hidalgo-Carvajal et al., 2021). At high TRLs, there is little progress that has been made at 8-9, meaning little commercial realization of the technology. This is probably because of the regulatory challenges and challenges in operations. For these systems to achieve commercial viability, research must address real-world issues in applications such as safety standards, customer readiness, and scalability (Yang et al., 2018).

Service innovation using AI and machine learning covers early to mid-TRLs (TRL 1-7), where there are significant achievements in the field of development & validation. While there is great potential for service innovation through AI, its practical applications are inhibited due to integration challenges and cost issues. For instance, while there is a demand for the development of predictive service models, few robust mechanisms to drive implementations that can be smoothly integrated into service industries are required (T. S. Baines et al., 2007; Visnjic et al., 2016).

Service-Oriented Business Models in PSS cluster represents significant advancement, with research and development on the verge of commercialization (TRL 4-9). Within PSS, service-oriented business models are common because they support both sustainability and customer engagement objectives (Heyes et al., 2018). Examples such as the “Product-as-a-Service” model encapsulate circular economic principles and have achieved higher TRLs, indicating their practical application capabilities. This specific approach benefits largely from more research that can make it refined and scalable for mainstream industrial adoption (Corti et al., 2013; Han et al., 2020).

Fundamentally, research in Sustainability and Circular Economy in Autonomous Service takes precedence in the early and mid-level TRLs, where the validation and business utilization are very minimal. Much of the research focuses on the theoretical perspective in embedding the principles of the circular economy into the services provided by autonomous services; very few go down to the level of practical investigation. The focus of future research should go into piloting sustainable autonomous services in realistic environments to bridge into commercial applicability (Hernandez, 2019).

This cluster illustrates a broad span of TRL distribution in figure 11, from foundational research into commercial applications. The AI and Machine Learning for Service Innovation cluster has the highest number of articles, with most at the Validation (TRL 6-7) stage. Operational optimization in service systems has the potential to improve efficiency and sustainability. If the research is to make a meaningful impact, then it needs to be directed at operational models that could achieve fast scaling and implementation within service systems in sectors prioritizing circularity and environmental goals. (Pieroni et al., 2019). Figure 12 highlights trends in research maturity across various technological domains.

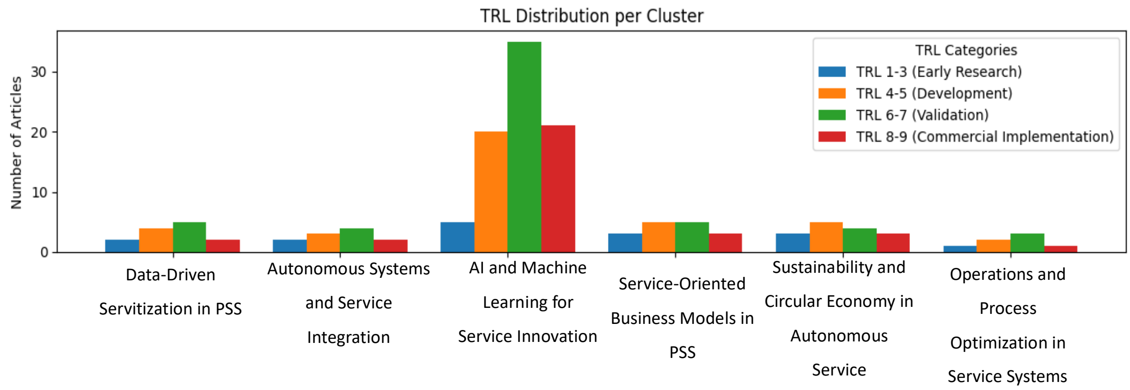

Figure 18. TRL distribution.

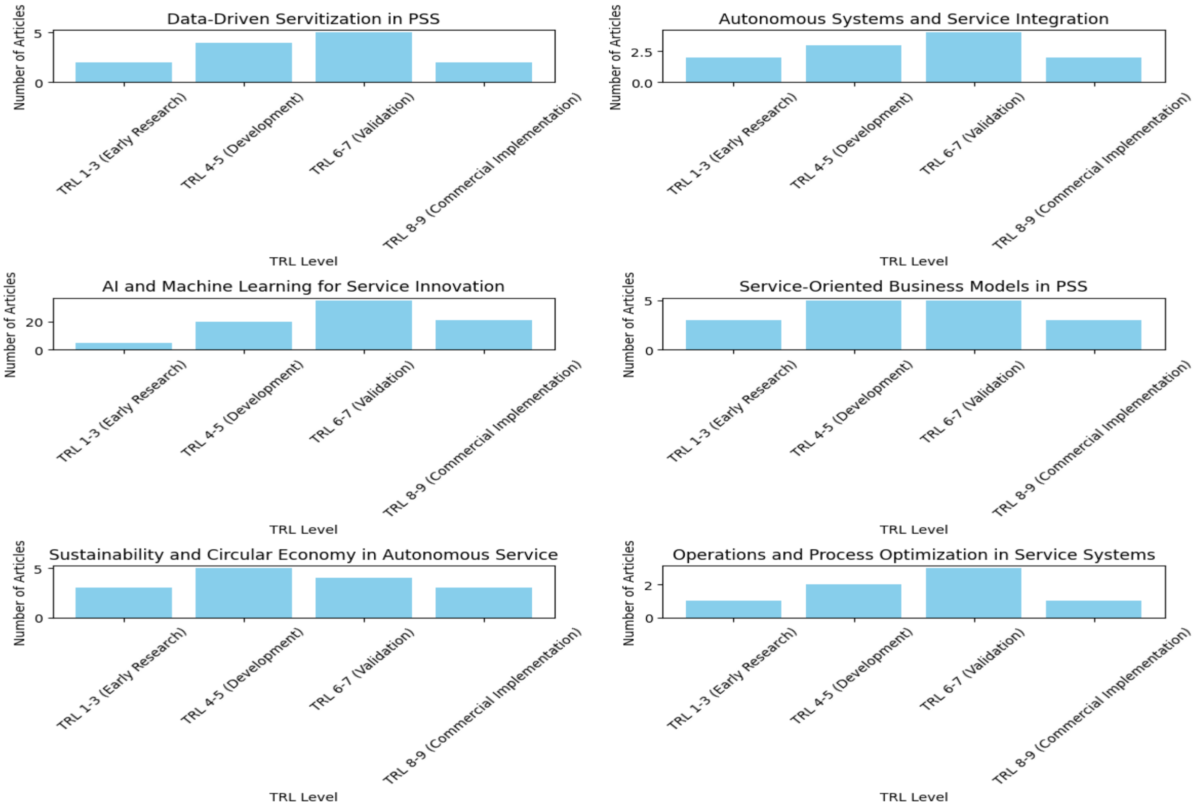

Figure 19. TRL distribution by individual cluster.

In table 2, technology readiness level has been demonstrated for different clusters. From 1 to 9, it was taken into consideration based on the research and maturity level.

Table 4. TRL distribution.

Cluster	TRL 1-3 (Early Research)	TRL 4-5 (Development)	TRL 6-7 (Validation)	TRL 8-9 (Commercial Implementation)	Remarks
Data-Driven Servitization in PSS	Moderate	Moderate	Moderate	Low	Even distribution across TRLs, indicating balanced research progression.
Autonomous Systems and Service Integration	Low	Low	Low	Very Low	Low articles count across TRLs, suggesting an emerging research area.
AI and Machine Learning for Service Innovation	Low	High	High	Moderate	High concentration in TRLs 4-7, showing maturity and readiness for practical application.
Service-Oriented Business Models in PSS	Low	Moderate	Moderate	Low	Balanced distribution, but fewer articles, indicating foundational yet diverse research.
Sustainability and Circular Economy in Autonomous Service	Low	Moderate	Moderate	Low	Even distribution, indicating research focus from foundational to validation stages.
Operations and Process Optimization in Service Systems	Low	Low	Low	Very Low	Consistent but low distribution across TRLs, indicating early and foundational exploration.

7. Discussion

The literature on autonomous solutions and servitization has evolved differently across industries and AI, IoT and automation technologies are converting traditional product-based business models to service-based models.

7.1 Theoretical contributions

This study explores how different companies can utilize AI to strengthen their capabilities and innovate their business models that enable autonomous servitization. This area needs to develop as the study is still underdeveloped. More research should be done to cover this gap (Bailey et al., 2019). This research also provides practical insights into the different stages of AI-driven business model innovation as companies move toward autonomous servitization. It provides some key contributions to the fields of AI, autonomous servitization, and business model innovation.

The first step is to understand the AI capabilities that industrial manufacturers need to move their businesses to autonomous and AI powered service models. The existing literature points out the fact that firms need to develop organizational capabilities to utilize AI and digitalization (Brock & Von Wangenheim, 2019; Burström et al., 2021). However, there is still a critical gap in understanding which specific AI capabilities are essential for industrial firms to build autonomous servitization solutions (Kohtamäki et al., 2019). In response to this gap, we performed systematic analysis of key themes that can provide industrial firms with the ability to provide autonomous product service. In order to find the most relevant topic clusters and investigate their evolution, we took advantage of BERT Clustering and TF-IDF Clustering. Both BERT and TF-IDF are techniques used in Natural Language Processing (NLP). We find that there are some interdependent AI capabilities that industrial manufacturers will need. Our study is one of the growing line of studies on the concept of autonomous servitization that contributes to how AI can create and capture value through digital service transformation.

By analyzing cluster evolution through Dynamic Topic Modeling, we reveal how AI-driven autonomous solutions evolve over time within servitization strategies. Based on some vocabulary of a research domain and its connected topics, and the closeness (proximities) of that vocabulary to the topics, we build the vocabulary of that domain and trace changes to the closeness (proximities) relationship between the vocabulary and the topics over time. Moreover, we studied the maturity of AI driven autonomous technology solution TRL for mapping its maturity in the context of servitization. From the study it can be seen that manufacturing firms are trying to shift from only selling products to offering equipment as a service (EaaS). In EaaS, autonomous production lines and AI driven predictive maintenance optimize the performance.

7.2 Rationale for Clustering Method

Table 5 compares two clustering approaches: TF-IDF + t-SNE and BERT-Based Clustering (BERTopic + HDBSCAN). BERT embeddings are used in BERT-Based Clustering that captured semantic understanding and BERT-Based Clustering relies on word frequency while TF-IDF relies on a combination of word frequency. The clustering algorithm for TF-IDF depends on exact word occurrences. ERT-Based Clustering utilizes HDBSCAN, which is a density-based clustering method. For dimensionality reduction, t-SNE is used whereas BERT-Based Clustering applies UMAP which is faster and more effective. TF-IDF + t-SNE is weak as it relies on keyword matching, whereas BERT-Based Clustering is strong due to its ability to capture semantic similarity. The number of clusters in the TF-IDF + t-SNE method must be determined manually, whereas BERT-Based Clustering automatically detects the number of clusters. So finally analyzing all of these, it can be stated that the best way to go with this clustering is to use BERT topic modeling techniques along with HDBSCAN.

Table 5. Comparison of TF-IDF and BERT method.

Feature	TF-IDF + t-SNE	BERT-Based Clustering (BERTopic + HDBSCAN)
Feature Extraction	TF-IDF (word frequency-based)	BERT Embeddings (semantic understanding)
Clustering Algorithm	keyword matching	HDBSCAN (Density-Based)
Dimensionality Reduction	t-SNE (slow, local structure only)	UMAP (faster, preserves structure)
Accuracy in Grouping	Weak (relies on keywords)	Strong (semantic similarity)
Number of Clusters	Manual	Automatically detected

From the clustering technique we get the six clusters automatically. Also, to cross check and validation we used VOSviewer.

7.3 DTM over Traditional Topic Modeling

Traditional topic modeling gives static topic distribution. On the other hand, Dynamic Topic Modeling represents topic evolution over time. Table 6 compares Traditional Topic Modeling and Dynamic Topic Modeling (DTM) across different aspects. The cases of traditional topic modeling are to identify the key topics within a data set, and DTM is to understand how topics evolve, grow and decay (Rabetino et al., 2021). Traditional Topic Modeling is best suited for general topic extraction, whereas DTM is more effective for analyzing trends over time. DTM can reveal when a topic gains popularity or declines. It helps to predict future research directions which is a critical advantage for fields like AI-driven servitization.

Table 6. DTM over traditional topic modeling.

Aspect	Traditional Topic Modeling	DTM (Dynamic Topic Modeling)
Time Consideration	Static (does not track changes over time)	Tracks topic evolution across time slices
Use Case	Identifying key topics in a dataset	Understanding how topics emerge, evolve, and decline
Best for	General topic extraction	Analyzing trends over time

The dynamic topic modeling illustrates the evolution of the six clusters. The Autonomous Systems and Service Integration cluster demonstrated by solid line in figure 17 demonstrates that the cluster was dominated during the period of 2000 to 2012. After 2012, it declined a little bit which indicated that initially this integration of this cluster was so high in the research field and later it turns out to the implementation. When it is in the implementation phase, then the research for this cluster is switching into specific portion like the customer or managerial behavior analysis or the impact of the implementation. From the research of the previous study, it is also obvious that the research related to autonomous systems and service was declining but gradually with the advancement of AI, it started growing (Kohtamäki et al., 2019; Kowalkowski et al., 2017; Naeem et al., 2024). The service-oriented model gradually increases from 2000 to 2013 and stabilizes after that. This stabilization indicates that models supporting digital and autonomous servitization became a long-term focus (Baines, 2015). It can be noticed that the AI and ML cluster has significant growth from 2008 to 2020, and it stabilizes. It indicates that the increasing use of AI-driven decision-making, predictive analytics, and automation in servitization (Kohtamäki, Brekke, et al., 2024; Sjödin et al., 2021). So, this visual representation in figure 17 is aligned with the existing research on autonomous solutions in digital business.

The sharp increase can be seen from 2006 to onward in data driven servitization. It represents the rise of big data analytics, IoT-enabled servitization, and digital twins. Operation and process optimization has a consistent but declining trend from 2000 to 2015. After 2015, this cluster stabilized. Early research likely focused on optimizing traditional service operations, while newer research explores digital and AI-enhanced efficiencies (Helo & Hao, 2022; Mathieu, 2001). Among all these clusters sustainability and circular economy grow steadily over the years particularly after 2010. It indicates that circular economy principles are being integrated into servitization models (Bocken et al., 2016; Lawrenz et al., 2021). Autonomous servitization is increasingly aligned with eco-friendly service models and carbon footprint reduction.

7.4 Effectiveness of TRL for Cluster Analysis

Technology Readiness Level (TRL) is a systematic scale used to assess the maturity of a particular technology from its initial conceptual phase to full commercial deployment. Using TRL we can evaluate the research trend, technological advancements and industrial adoption (Hasanah et al., 2020). It highlights the important research area. It helps to visualize the progression of the research. TRL 1-3 means that those articles have discussed basic principles and initial feasibility is tested. It is called early research stage. After that, TRL 4-5 or development stage which creates prototypes and lab scale experiments. The next stage is TRL 6-7 or validation stage where plot scale and real-world validation of technology in operational environments are performed. And the last one is TRL 8-9 or commercial implementation and in this stage, full scale deployment and commercialization are completed (Blichfeldt & Faullant, 2021; Miller et al., 2016).
From the figure 18, it can be shown that the AI and machine learning cluster has the highest number of articles. Among those articles majority of the articles are in the development phase TRL (4-5) and commercial implementation phase TRL (8-9). There are very few articles that are in the early research stage. This indicates that this cluster is one of the dominated clusters. To know more about the other clusters, if we look into the autonomous systems cluster, it can be visualized that articles are fairly evenly distributed across all TRL level. Autonomous systems with service cluster are more focused on the development stage which means TRL (4-5) and validation (6-7) stage. The data driven servitization cluster articles are distributed across all TRL levels. All the distribution are equal. At the same time, service-oriented business model articles are well distributed across all levels. But it has slightly more focus on development (TRL 4-5) and validation (TRL 6-7). Sustainability and circular process are evenly spread across all TRL levels. It shows more concentration in the Development (TRL 4-5) and Validation (TRL 6-7) phases like the previous cluster. This means that these fields are actively evolving but not yet fully commercialized (El-Gohary & Eid, 2013). Lastly, the Operations and Process Optimization in Service Systems has a balanced distribution across TRL levels. It demonstrates a mix of research and implementation (Lokuge et al., 2019).

7.5 Aligning TRL with DTM in AI-Driven Business Services

To explore the evolution and maturity accurately, we can intergrate dynamic topic modeling (DTM) along with technology readiness level (TRL) for better understanding about how research themes in autonomous servitization have evolved. Through DTM we can know whether a topic is growing, stabilizing or declining while TRL assesses the maturity and industry adoption potential of each theme. The combination of both will provide a better understanding of the thematic evolution.

The hottest and most commercial area is AI and machine learning for service clusters. It shows a strong upward trend in research and industry applications. AI powered service and autonomous decision making have transitioned from theoretical exploration to high TRL implementation. Data driven servitization has gained similar attention because of the IoT, big data analytics and digital twins that make the path easier for real world service (Saura et al., 2024; Wessel et al., 2024). This field is not strong like AI and ML. It is balanced between foundational and applied research. But the commercial adoption is increasing gradually.

On the other hand, autonomous systems and service clusters show a cooling trend which means that research in this area has matured enough. The reason is autonomous technologies are now widely integrated into service ecosystems (Fottner et al., 2021; Zis et al., 2023). The same applies to service-oriented business models which remain evergreen trend. This indicates that companies have largely adopted servitization strategies (Kohtamäki et al., 2021). Now they are shifting their focus to optimization rather than reinvention. In the sutainability and circular economy cluster, we can see the warming trend. This area is still in the early to mid TRL phase. There is a huge scope to reduce the gap between theoretical framework and practical applications for sustainability (Klein et al., 2020; Leone et al., 2021). We can look for AI driven circular model in servitization. Lastly, the operation and process clusters demonstrate a cold trend. It indicates a decline in research interest. This is happening because the AI driven decision-making techniques are absorbing traditional models.

7.6 Limitation and Future Research

Most of the conceptual models and frameworks proposed (business model typologies, process frameworks, classification matrices) are principally theoretical or based on only limited qualitative evidence. The AVS taxonomy and servitization models by Leminen et al. (2022) come from empirical cases. But the notion of 'fluidity' in business models is new and not studied over time. Rather, it is presented in terms of concepts and theory and is not based on real world changes (Leminen et al., 2022). Like past case studies, Sandvik et al. (2024) framework for disruptive market shaping is similar. Though it does not clearly compare successful cases with failed ones (Sandvik et al., 2024).

Another theoretical gap lies in frameworks for determining the appropriate level of autonomy. Fottner et al. (2021) ask if the highest level of automation is always the best, and if not, whether theory is needed of the conditions under which less autonomy (or human in the loop designs) would result in better outcomes (Fottner et al., 2021). We currently don’t have robust theoretical models or decision tools that are sensitive to factors such as complexity, variability, strengths of the human vs. strengths of AI, cost, and risk that can suggest the “best level of autonomy” for a given process or service. Such a theory would allow managers, for instance, to decide what tasks should be completely automated, and for what to retain in human control for optimal overall performance.

Turienzo et al. (2023) highlights a shift from B2C to B2B as servitization expands. It reflects a broader challenge to traditional economic and management theories about value and ownership (Turienzo et al., 2023). Autonomous service models create new dynamics. It is necessary that existing theories of firms, transaction costs, and product service systems serve in new lights. They must take into consideration new ways of sharing assets and risks. This idea also appears in many of the studies but is not always discussed directly. Beck et al. (2022) also discuss the paradox of autonomy in organizations. The relationship between principal and agent transforms because an AI system functions as the agent instead of a human agent (Beck et al., 2022).

From the research it can be observed that several studies rely on qualitative methods (interviews, case studies, conceptual reasoning) due to the emergent nature of the topic. This provides a good basis for theory building but lacks quantitative validation. In particular, Sandvik et al. (2024) explicitly encourage quantitative studies to test the robustness of their four market-shaping dimensions and argue that this could be facilitated by the creation of measurement scales and use of surveys or statistical analysis on a larger sample (Sandvik et al., 2024). Autonomous technology together with its market effects show rapid modifications which make time an essential factor. The study requires continued data collection from repeated case studies in combination with firm surveys for identifying these changes and their underlying factors.

Future studies should investigate autonomous service integration in a wider array of industries and regions. As technology progresses, researchers should be ready to study fully autonomous operations. Autonomous swarms and multi-agent coordination deserve special attention, since they represent a frontier where the system of services might exhibit properties (Maisenbacher et al., 2014). Long-term monitoring of such systems, when they become available, will help validate ideas like business model fluidity or granular system value logic in practice. Long-term system monitoring when available will validate practical applications of business model fluidity and granular system value logic (Demirkan & Delen, 2013). Research should make further efforts to understand better the social and human elements which science currently lacks clarity about. We can conduct longitudinal surveys or ethnographic studies of communities and organizations adopting autonomous systems to see how attitudes and practices change over time.

Decision models that incorporate technical feasibility, cost-benefit, risk, ethical implications, and human factors can be developed in future to recommend an autonomy level. Also, to facilitate quantitative research, scholars should work on developing reliable measurement instruments for key constructs in this domain. Sandvik et al. (2024)

demonstrated that dimensions (value shaping, demand nurturing, etc.) can be turned into survey scales by operationalizing each (Sandvik et al., 2024). Longitudinal case tracking and databases can also be used to enhance the quality of the work. To directly study human interaction with autonomous systems, experimental methods from psychology and HCI (human–computer interaction) should be employed. And finally, more interdisciplinary research should be carried out to improve the proper use of autonomous service systems.

8. Conclusion

This study explores the integration of autonomous solutions within servitization models. The findings highlight the need for advancement of autonomous technology to reduce costs, make data driven decisions and to adopt sustainable practices. The relations between the clusters are indicative of a convergence in research narrative from foundational to frontiers.

Data text mining was used to analysis the articles from Scopus. Data text mining can quickly analyze large volumes of research articles. It helps to identify connections between servitization and autonomous solutions. It reduces biases in identifying trends or patterns and saves time and effort compared to manual reviews, especially for mapping vast academic fields. TF-IDF and BERT basec topic modeling are used to cluster articles. Among these two techniques the best one has been chosen for further analysis. For our study the best is BERT based topic modeling because it has been trained on a massive corpus and fine-tuned for specific tasks. Both BERT and TF-IDF are techniques used in Natural Language Processing (NLP). TF-IDF is a statistical method used to represent text numerically and BERT is a deep learning-based NLP model.

This study provides ideas to advance research in the field of servitization for autonomous solutions by analyzing its trends. Topic modeling can be used in several ways to create clusters of the scholarly field. It helps to identify the popular or emerging topics that are gaining interest. They can also revive less discussed or fading topics by redefining them. Also, weak or overlooked topics can be made more relevant by applying fresh theories, perspectives, or levels of analysis. In our study we have chosen dynamic topic modeling over traditional topic modeling. Because it is successful for analyzing trends over time which traditional cannot.

The six identified clusters represent key advancements in autonomous servitization and digital transformation. Autonomous systems have been integrated with success in an optimal way to decrease human intervention and optimize processes to improve service delivery. Service-oriented business models have enabled firms to shift from traditional product-based approaches to value-driven servitization. Data-driven servitization allows companies to use real-time data to create better and more profitable services. AI and machine learning improve service quality by creating smart decision-making and automation. With AI and Process optimization, the operations become smoother, cost reduction and scalability improved. Sustainability and circular economy practices help businesses reduce waste and make services more eco-friendly.

In thematic analysis, TRL provides a structured way to align autonomous technologies with servitization needs, ensuring feasibility, reducing risks, and identifying gaps between innovation and application in service-oriented business models. We have used TRL in this research to know about the maturity of the research and adaptation of the articles. Technology Readiness Level (TRL) is important for evaluating the maturity of autonomous solutions in servitization. It helps researchers to understand whether technology is ready for real-world implementation or still in development. Using both DTM and TRL for the analysis of the autonomous service integration literature study, we are able to get the real scenario and the actual trends which will be used for future research and analysis. So, this study contributes to a deeper understanding of autonomous servitization’s current state, the research gap of the existing studies and future directions.

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