International Journal of Innovative Research and Scientific Studies, 9(1) 2026, pages: 51-58

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Transition to a smart service lifecycle management model with artificial intelligence and data analytics

Mehmet Ümit Gürsoy[1*], Mehmet Kurt[2]

[1]*Mechanica Yapay Zeka Teknolojileri Sanayi ve Ticaret A.Ş., İzmir, Türkiye.*
[2]*İstanbul Health and Technology University, Software Engineering Department, İstanbul, Türkiye*.

Corresponding author: Mehmet Ümit Gürsoy (*Email: mugursoy@gmail.com*)

Abstract

In service-based industries, sustainable competitive advantage is closely related to the continuity, quality, and adaptability to innovation of the services offered to customers. As service systems become increasingly complex due to the impact of digital transformation, Industry 4.0, and increasing competition, traditional Service Lifecycle Management (SLM) systems are insufficient to meet emerging operational and customer demands. Therefore, a different approach to SLM systems using current technologies has become a major necessity. This research aims to examine how SLM can be algorithmically improved through the systematic integration of data analytics (DA), machine learning (ML), and artificial intelligence (AI) into service management stages, and to explore the intelligent management system provided by this transformation. Adopting a conceptual and analytical approach, this research proposes a different approach to the Intelligent Service Lifecycle Management (SSLM) model by integrating intelligent technologies into the fundamental stages of the classical SLM framework. The findings demonstrate that DA, ML, and AI-supported SLM transforms service management from a reactive and static structure into a proactive, predictive, and data-driven system. It also improves decision-making accuracy, risk mitigation, and resource optimization throughout the service lifecycle. Consequently, service-based organizations will be able to achieve higher operational efficiency, improved service quality, and increased organizational agility through SSLM.

Keywords: Artificial Intelligence (AI), Data Analytics (DA), Digital Transformation, Machine Learning (ML), Service Lifecycle Management (SLM), Smart Service Lifecycle Management (SSLM).

DOI: 10.53894/ijirss.v9i1.11147
Funding: This study received no specific financial support.
History: Received: 14 November 2025 / **Revised:** 24 December 2025 / **Accepted:** 29 December 2025 / **Published:** 8 January 2026

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Today's rapidly evolving and changing business environment must cope with intense competition. This competition brings various challenges across fields of activity. Service-focused organizations are among these activities. This is because traditional management methods related to the services, they offer struggle to manage business processes and are insufficient in improving service quality. Therefore, considering the service itself as a product is gaining importance. Not only commercial businesses providing services, but also public institutions want to diversify and improve the services they offer. These organizations aim to increase public satisfaction with new services in addition to those they currently provide. However, the increasing number of people and the complexity of the variety of services needed make the process difficult for these organizations to manage. They struggle to maintain the quality standards of the services they provide. Service management, drawing on experience gained from similar service management systems created previously, has taken its current form by being specifically developed and adapted for the service sector. Thus, studies that started in specific areas of the sector have been generally extended and made more systematic.

Although the concept of service may not initially resemble physical products, when considered as a process, it shares many similarities. An approach like Product Lifecycle Management (PLM) [1] which focuses on the manufacturing industry, has been adapted to the service sector [2]. Service Lifecycle Management (SLM), which encompasses all processes from the concept stage to design, market launch, operational management, and continuous improvement, has been developed over time [3].

The manufacturing industry, recognizing its need for the service sector to meet its production process requirements, has invested in service management. These investments have contributed to the development of service management systems. This allows the manufacturing industry to find new business opportunities and reach different customers. This change has paved the way for the combined use of PLM and SLM. Product Services Systems (PSS) were designed and implemented with this approach [4]. PLM is a system for managing a company's products most effectively throughout their entire lifecycle. SLM, on the other hand, represents the coordination and management of activities throughout the service lifecycle, thus establishing an organic link with products.

The relationship between management information systems and Industry 4.0 is a significant factor in explaining the subject's intriguing nature. This necessitates examining Industry 4.0 from the perspective of management information systems [5]. Increased global competition, driven by digital transformation and the widespread adoption of Industry 4.0 technologies, is intensifying the need for all firms to accelerate their digital transformation. Thanks to the Industrial Internet of Things (IIoT), factory production processes can be optimized through predictive maintenance and similar applications.

The use of SLM systems in conjunction with PLM systems has become a necessity for many industrial products in extending their lifecycles [6]. Most products launched on the market may require regular or condition-based maintenance throughout their lifecycles. The integration of SLM and PLM systems in managing these maintenance tasks improves process management. Furthermore, advancements in predictive maintenance technologies enable increased product lifecycles and operational efficiency [7].

Most factories and businesses require large and small service operations in their production processes. The availability of parts for complex products to be assembled on assembly lines is ensured through small service operations within the factory. This necessitates the use of different management systems in product manufacturing. Improving production and service processes is also crucial for the continuity of businesses. Artificial intelligence and data analytics applications in managing the volume of personalized data generated in SLM accelerate operational processes and simplify management.

In addition to manufacturing the product or providing the service, product development and smartening efforts are enabled by systemic advancements. Service-Oriented Product Systems (PSS) are essential for bringing smart products to life. This necessitates the combined, harmonious use of traditional PLM, SLM, and software-oriented Application Lifecycle Management (ALM). The overall functionality of smart products is a combination of mechanical, electronic, and software components.

The development of intelligent products and services requires systematic use of PLM, ALM, and SLM together. However, using different lifecycle models and various toolchains for the same product creates inefficiencies and can lead to inconsistent data management. To overcome these challenges and prepare for rapid market competition, it is important for manufacturers to have efficient product lifecycle processes and shared data centers [8]. This is possible by integrating and working together with other systems through a core system, according to the structure of the product that business brings to market.

In today's digital ecosystem, with the advent of the Internet of Events (IoE), the volume of data (Big Data) is expanding, offering significant opportunities for businesses. However, this also brings with it the challenge of managing and analyzing this data [9]. In this context, Artificial Intelligence (AI) and Data Analytics (DA) play a crucial role in optimizing both SLM and PLM/SLM integration [10].

The service sector is rapidly growing thanks to technologies like IoT. This increases the diversity and complexity of data. Companies can use the insights gained from this data to make their service processes more agile, predictable, and customer-centric. Thus, service sectors have seized the opportunity for rapid growth in global economies.

As the complexity of services increases, managing all stages of the lifecycle effectively and in a data-driven manner becomes crucial. The SLM concept is particularly important for small and medium-sized enterprises (SMEs) and large organizations alike that provide these services.

Public institutions and organizations, such as hospitality businesses or municipalities, need to continuously manage and improve the value and quality of the services they offer [11]. Furthermore, regardless of business size, traditional SLM approaches are largely based on manual decision-making processes, which don't provide sufficient opportunity for data-driven dynamic optimization. Traditional methods often fail to adapt to real-time data, customer behavior patterns, and operational fluctuations. However, advancements in AI and DA make it possible for every stage of the service lifecycle to be automated, predictable, and responsive to customer behavior. Recent developments in AI, machine learning (ML), and predictive analytics have provided opportunities to improve service design, delivery, maintenance, and processes.

2. Service Lifecycle Management

Service lifecycle management (SLM) can be addressed with different models depending on the scope and sector. One of the best-known and most generally accepted approaches is the ITIL (Information Technology Infrastructure Library) model, which was specifically developed for the IT (Information Technology) sector [12]. Although this model was designed for IT services, it has been adapted to general service management over time [13].

2.1. ITIL: Information Technology Infrastructure Library

IT service management (ITSM) evolved naturally as services became underpinned in time by the developing technology [14]. According to the ITIL model, SLM consists of five phases that optimize the value creation process of a service [15]. These phases, supported by digital tools, have the potential to increase service quality and efficiency. ITIL also forms the backbone of the SLM system.

Table 1.
ITIL Service Lifecycle Phases.

	Phase	Focus	Objective Summary
1	Service Strategy	Why are we doing this?	It establishes the core strategy that determines how IT services will support business objectives and compete in the market.
2	Service Design	How will it be done?	It enables the design of new or modified services, processes, architecture, and measurement methods in line with the strategy.
3	Service Transition	Go-live	It manages the successful, secure, and minimally disruptive deployment of the designed services to the operational environment.
4	Service Operation	Periodic Operation	It ensures that services operate efficiently and effectively on a periodic basis, and that agreed service levels are met.
5	Continual Service Improvement	How can we do better?	By continuously evaluating the performance of services and processes, it identifies and implements improvement opportunities according to defined goals.

This diagram illustrates the value-oriented and continuous improvement-focused structure that forms the basis of the ITIL framework.

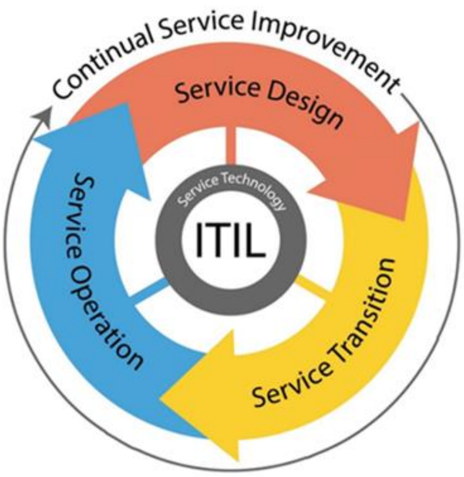

Figure 1.
The ITIL Service Lifecycle Diagram.

The ITIL Service Lifecycle diagram shows the flow of a service from its initiation with a strategic decision, through its design, implementation, daily operation, and continual improvement. This visualization emphasizes that the Phase of ITIL are not merely a linear process, but a continuous cycle of improvement.

2.2. SLM: Service Lifecycle Management

ITIL provides an example of a service lifecycle model. Similarly, the general scheme of SLM, which has been developed in a more general and comprehensive way, is shown below.

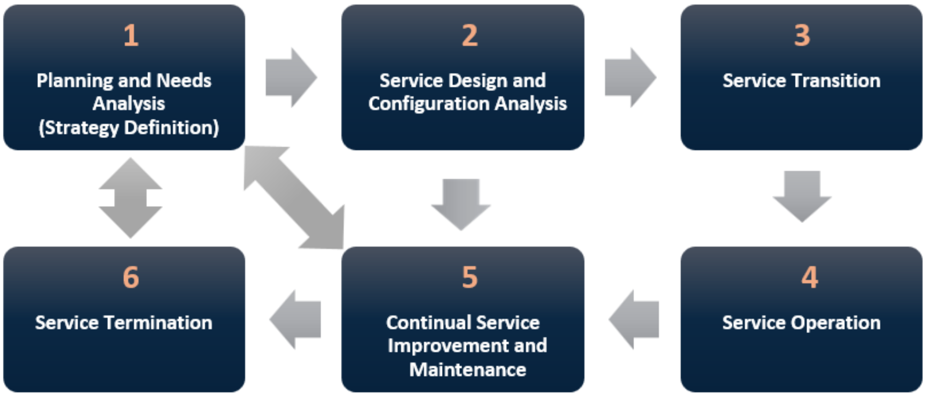

Figure 2.
Service Lifecycle Management Diagram.

Service Lifecycle Management (SLM) is a holistic approach that enables the structured and systematic management of a service from its initial conception to its termination. The process begins with the Planning and Needs Analysis (Strategy Definition) phase, during which the purpose, scope, and strategic objectives of the service are defined. This is followed by the Service Design and Configuration Analysis phase, where the technical, operational, and structural requirements of the service are determined and the design is finalized. Next, during the Service Transition phase, the designed service is tested and deployed into the live environment in a controlled manner. Once the service goes live, it enters the Service Operation phase, where it is delivered, monitored, and managed daily. Performance data and feedback collected during service operation are then analyzed in the Continual Service Improvement and Maintenance phase to enhance service quality, efficiency, and sustainability. Finally, when the service no longer delivers sufficient value, it proceeds with the Service Termination phase, during which it is systematically and controllably retired.

This diagram also illustrates how the connections between the stages of the SLM are related. This type of relationship shows the nature of the inter-stage link. This, in turn, expresses the connection between the different phases within the service's lifecycle.

2.2.1. Planning and Needs Analysis (Strategy Definition)

At this stage, strategic planning and needs analysis are conducted to determine the service's position in the market. The target customer group and how the service will create value are identified. In the digital age, strategic decisions are made through the interpretation of historical data and predictive analysis. The role of AI in Management Information Systems is to enable decision-makers to make informed decisions by accessing accurate and timely information. Thus, the service strategy can be proactively determined according to the current and future needs of the market. This is the stage where the business determines which services to offer, to whom, at what cost, and how, and where goals and policies are defined.

2.2.2. Service Design and Configuration Analysis

This is the stage where the service is meticulously planned in line with strategic goals and confidently transferred to the operational environment. Literature shows that data mining and Natural Language Processing (NLP) techniques are frequently used to anticipate customer needs during the service design phase [16].

Digital components, such as Cyber-Physical Systems, are added to service design to ensure the harmonious functioning of both the physical and digital aspects of the service. During service design, feature extraction from customer feedback, feature extraction through sentiment analysis, and the automatic generation of service delivery diagrams are all achieved through AI.

2.2.3. Service Transition

It manages the secure deployment of designed or modified services to the live environment. It is tested in a virtual environment using AI-powered testing and validation tools. Potential errors and risks are minimized before the service is deployed live. The security and speed of the transition are improved.

2.2.4. Service Operation

This is the stage where the service is delivered daily, and user requests and problems are managed. Ensuring uninterrupted delivery service and minimizing costs is a priority for businesses. Customer feedback is collected during delivery. This data provides valuable information for improving the process. Digital transformation benefits at this stage include increasing service efficiency and cost-effectiveness. AI-based systems automate repetitive and routine tasks. This reduces human intervention, lowers errors, and increases productivity. In service delivery, AI is applied in areas such as process mining, intensity estimation, and workload optimization.

Public service providers, such as municipalities, facilitate service delivery by incorporating AI into decision-making and operational processes through digital transformation offices. AI is used to increase autonomous service interactions and improve the service process through chatbots.

In queue management, ML (Machine Learning) models are used to increase decision-making efficiency. By building models with queue theory, queue length and waiting times can be predicted, leading to improvements. Optimal decisions can be made regarding the number of personnel and machines needed for service delivery. It is used to estimate waiting times, plan capacity, and analyze service congestion.

2.2.5. Continual Service Improvement and Maintenance

The final stage of SLM (Service Level Management) is based on the continuous measurement, monitoring, and improvement of services. This stage ensures the cyclical nature and sustainability of the service. System performance and processes are continuously measured, evaluated, and improved throughout the service operation.

The strongest area in literature at this stage is predictive maintenance and anomaly detection. With machine learning, failure prediction, customer churn probability analysis, prediction of service level agreement violations, implementation of improvement plans, service reporting, and process maturity management analyses can be performed.

At the same time, data-driven improvement, using AI and DA (Data Analytics), enables rapid analysis of accurate, functional data needed for improvement by continuously monitoring the service's key performance indicators (KPIs). In services such as distance education, AI-based measurement systems play a significant role in identifying students' individual differences and learning styles. This type of personalized data not only improves the service but also provides crucial data input for the Service Design stage in the next cycle.

2.2.6. Service Termination

At the end of the service lifecycle, an analysis of service costs is conducted, and service efficiency is evaluated based on user behavior. Data generated during the service process is analyzed using AI to assess service efficiency and decide whether to terminate or revise the service.

2.3. The Role of Artificial Intelligence and Data Analytics in SLM Optimization

In the context of Management Information Systems (MIS), AI plays a central role in providing accurate and timely information for managers to make informed decisions. Data Analytics is a fundamental method for providing this information. This method allows us to derive meaningful conclusions from numbers and figures. In both industrial and social settings, DA optimizes the entire structure from root to end, ensuring continuous productivity improvements. Data analytics models used in SLM include:

2.3.1. Descriptive Analytics

It is used to transform raw data into summarized and understandable information. Insights from large datasets are presented through tables, graphs, and reports. Business intelligence tools and data visualization tools are used. It enables SLM to understand its operational status and past events by interpreting feedback.

2.3.2. Diagnostic Analytics

Diagnostic analytics performs root cause analysis by first answering the question "what happened" and then asking, "why did it happen?". This process involves examining relationships and dependencies and searching for anomalies or outliers. It uses data mining, in-depth analysis, correlation, and regression techniques.

During strategy and transition phases, it is used to predict future trends and risks. This, in turn, guides service or product production, thereby increasing business profitability.

2.3.3. Predictive Analytics

It aims to predict future outcomes or trends using past data. It doesn't say exactly what will happen, but it indicates the probability of an event occurring or the expected range of an outcome. Machine learning (ML) algorithms, especially regression and classification models, are used in time series analysis.

2.3.4. Prescriptive Analytics

This is the most advanced stage of analytics. After understanding both the past and the potential future, it suggests the most appropriate step or decision to take to achieve a specific goal. It is the area where Artificial Intelligence (AI) is most widely used. Tools such as optimization algorithms, simulation, AI systems, and decision trees are employed.

Throughout the entire cycle, it provides direct optimization by identifying the best course of action. It answers the question: Which resource should we allocate and when?

3. Optimization of SLM Stages with Artificial Intelligence and Data Analytics

AI and DA modify each stage of SLM, leading to significant improvements in service management and ensuring seamless process execution. AI-powered adjustments within the system allow for continuous optimization of the entire system over time, resulting in consistently improved overall system efficiency.

3.1. Optimizing Predictive Decision Making in the Strategy Phase

Service strategy defines the fundamental principles for market presence and competition. Traditional methods generally rely on historical data. However, with the impact of the digital world, DA leverages the power of information from the past to shape the process for the future. To forecast demand and plan capacity, AI algorithms can analyze big data such as seasonal changes, economic indicators, and customer behavior, predicting future service demand with high accuracy.

In hotel management, DA determines the most appropriate strategy for room pricing and occupancy rates. In municipalities, it ensures accurate planning of services such as emergency services or public transportation capacity.

The risks of launching a service can be simulated using AI-based models. This allows for the optimization of the return on investment (ROI) of strategic investments from the outset. Strategic units, such as the Digital Transformation Office, contribute to digital transformation by positioning AI and DA as important tools, aligning service strategy with the organization's overall digital vision.

3.2. Smart Infrastructure and Risk Mitigation Optimization During Design and Transition Phases

The design phase, which determines how the service will be delivered, and the transition phase, which translates this into operation, become smarter and more error-free with AI and DA. Cyber-Physical Systems, which form the basis of Industry 4.0, mediate the integration of physical and digital components into service design.

During the transition phase, the testing of new service processes is simulated using AI-powered automation tools (RPA). This allows for the identification of potential errors and bottlenecks before the service is deployed to the live environment, significantly reducing the risk and cost of the transition.

In services like distance education, AI algorithms are used during the design phase to establish data collection mechanisms that identify individual differences.

3.3. Automated Proactive Management Optimization During the Operational Phase

Operation is the stage where the value of the service is actually delivered and consumed. AI and DA optimize two key areas here.

3.3.1. Process Automation

These are AI-powered automations that automate the workflow during service delivery and simplify the implementation process. Digital transformation also impacts HR (Human Resources) processes. This is especially true for routine tasks, such as payroll and initial applicant screening, which can be automated with AI-powered robotic process automation (RPA). Chatbots and virtual assistants automatically resolve simple requests 24/7. This allows human resources to focus on more complex issues, reducing operational costs.

3.3.2. Error and Outage Management

Sensor data collected from machines and systems via IoT is displayed and stored. The stored data is analyzed with DA, and an AI model is trained. This model can predict potential equipment failures that could lead to service interruptions through real-time analysis during system operation, initiating the repair process without downtime. This prevents interruptions in the process, minimizing costs and increasing operational efficiency.

3.4. Optimization of Circular Learning in the Continual Service Improvement Phase

CSI is the most critical, iterative phase of SLM. AI and DA transform this phase from a mere measurement activity into a learning and automated adaptation mechanism. AI algorithms can quickly extract root causes affecting service efficiency and customer satisfaction from data sets that are too complex to be identified through manual analysis. This allows for accurate decisions on which improvement projects should be made to maximize efficiency. Particularly in service sectors such as education, monitoring individual learning styles and performances with AI enables the dynamic adaptation of services to the individual. This personalization output is used as feedback in the Service Design phase in the next cycle. Similarly, in higher education, the aim of digital transformation is not only to guide students towards knowledge but also to create interactive learning environments. CSI measures the effectiveness of these environments and ensures their continuous improvement with AI.

4. Transformational Impacts of AI and Data Analytics-Optimized SLM

4.1. Cost Efficiency and Resource Optimization

This effect focuses on eliminating waste (time, labor, money, etc.) that occurs during service delivery. Chatbots or RPA automation minimize the waste of human and technological resources during the operational phase.

SSLM improves workforce efficiency, particularly by automating repetitive tasks during the service operation phase [17]. These tasks include simple incident management, demand fulfillment, and routine system checks.

DA predicts future service demand with high accuracy by analyzing past demand patterns. This enables accurate capacity management during the service strategy and service design phases.

4.2. Proactive and Predictive Management

The operational and strategic phases of SLM shift from a "reactive" to a "proactive" structure. This is a significant factor in increasing citizen satisfaction, especially in public services. AI and DA transform SLM from a system that merely reports the past into a structure that predicts the future.

Predictive analytics analyzes real-time data from service systems (IoT devices, servers, software logs). This detects signs of failure or service disruption in advance. It shifts the incident management process from "responding when an incident occurs" to "warning and preventing incidents before they happen." Particularly in public services, DA can predict where a service will fail by modeling user behavior (complaint trends, frequency of service use). This is a significant benefit in increasing citizen satisfaction.

4.3. Complete Improvement in Service Quality

Traditional improvement efforts often focus on the most obvious symptoms. AI and DA enable finding the source of the improvement. Accurate and in-depth data analysis from the CSI phase ensures that improvements are directed not at symptoms, but at the root causes of service quality issues.

Diagnostic analytics quickly processes event and problem data, finding complex relationships and patterns that human analysts might miss. In the CSI (Continuo Service Improvement) phase, improvement efforts focus on recurring and underlying causes of failure in the system, rather than "treating symptoms."

AI analyzes unstructured data (call logs, emails, social media comments), providing more accurate and in-depth insights for CSI into what the customer truly values and what aspects of the service are causing them dissatisfaction.

4.4. Organizational Agility

Agility is the ability to quickly adapt to market changes or meet new customer expectations. AI-powered SLM (SSLM) helps organizations adapt to these changes more quickly.

AI-powered data collection and analysis shorten the feedback loop between service design and service transition phases. Performance data is instantly analyzed immediately after a new service is launched, and adjustments can be made quickly.

Predictive analytics shortens decision-making time by suggesting the best course of action in situations where the organization needs to act quickly, such as a major security breach or competitor move.

4.5. The Importance of Data Management

The foundation of all these transformations is the proper management of data. The main requirement for optimization is the rapid analysis of data generated throughout the lifecycle using appropriate and functional methods. This requires a robust data management infrastructure to make informed decisions.

The integrated structure of SLM necessitates the collection of all data (service costs, customer experience, operational performance, etc.) from PLM and other service systems in a single central environment. Since AI and DA operate with large and diverse data volumes (including sensor data from IoE), a robust data management infrastructure to store, process, and analyze this data at high speed is critical. Incorrect or inadequate data management leads to erroneous results from AI/DA models and renders all optimization efforts futile.

AI and DA fundamentally change the management philosophy of a service organization by not only making SLM work a little better but also preventing problems before they arise, avoiding resource waste, and radically improving service quality based on scientific data. Therefore, they create a transformative impact.

5. Conclusion

5.1. Smart Service Lifecycle Management (SSLM)

In service-based economies, continuity, quality, and efficiency are vital for competitive advantage. However, traditional management models make these elements unsustainable. This situation has transformed Service Lifecycle Management (SLM) from merely a management model into a necessity for service-providing businesses. This study demonstrates that integrating Artificial Intelligence (AI) and Data Analytics (DA) is a key element in transforming this necessity into a powerful competitive advantage. The article shows how these technologies have gone beyond optimizing SLM and have transformed it into a new management concept, Smart Service Lifecycle Management (SSLM), similar to PLM with AI [18].

AI impacts every stage of SLM, from strategy to operation, providing a significant transformation. It digitizes strategic decisions, making them data driven. It proactively automates service operations with predictive analytics. It reduces transition risks and supports the Continuous Improvement cycle with specific data. SLM provides a roadmap for service-providing businesses to manage their assets with a systematic, cyclical, and strategic approach. Digital transformation, on the other hand, creates opportunities to increase the value of services through AI and DA.

5.2. Theoretical Contribution and Managerial Implications

This study provides a comprehensive review of the role of artificial intelligence in service lifecycle management. One of the most important managerial implications of this article is that the success of AI-powered SLM lies in transforming organizational culture from reactive to proactive management. Whether it's creating a flawless guest experience in hospitality or providing citizen-centric smart services in municipalities, successful service management relies on establishing a continuously learning and evolving structure by feeding all processes, from strategy to operation, with AI and data. This integrated approach increases the efficiency of businesses while also ensuring competitive advantage and long-term sustainability.

5.3. Future Research Areas

This study predicts that the SSLM model can be applied in different service sectors. Future research could focus on validating this model through sector-specific case studies. However, attention should be paid to the ethical issues, algorithmic bias risks, and data management challenges that service providers face when integrating AI algorithms into SLM processes.

In conclusion, despite these challenges, Smart Service Lifecycle Management (SSLM) offers a crucial management model for the survival and thriving of the service sector in the digital age. It is projected to successfully guide both academic and industrial research in the future. SLM will become increasingly necessary for service businesses. Artificial Intelligence and Data Analytics will be key elements in transforming this necessity into a competitive advantage.

References

[1] J. Stark, *Product lifecycle management (PLM), In: Product lifecycle management (volume 1)", decision engineering*. Cham: Springer, 2022.

[2] S. Ötleş *et al.*, "Product lifecycle management (PLM)," *Plastik & Ambalaj Dergisi*, pp. 36-45, 2015.

[3] M. Fischbach, T. Puschmann, and R. Alt, "Service lifecycle management," *Business & Information Systems Engineering,* vol. 5, no. 1, pp. 45-49, 2013. https://doi.org/10.1007/s12599-012-0241-5

[4] A. Deuter, A. Otte, M. Ebert, and F. Possel-Dölken, "Developing the requirements of a PLM/ALM integration: An industrial case study," *Procedia Manufacturing,* vol. 24, pp. 107-113, 2018. https://doi.org/10.1016/j.promfg.2018.06.020

[5] H. Akıncı and Ü. G. Kahraman, "Industry 4.0: An evaluation from the perspective of management information systems," *Mehmet Akif Ersoy Üniversitesi Uygulamalı Bilimler Dergisi,* vol. 8, no. 1, pp. 76-99, 2024. https://doi.org/10.31200/makuubd.1442339

[6] S. Wiesner, M. Freitag, I. Westphal, and K.-D. Thoben, "Interactions between service and product lifecycle management," *Procedia Cirp,* vol. 30, pp. 36-41, 2015. https://doi.org/10.1016/j.procir.2015.02.018

[7] M. Gürsoy, U. Çolak, M. Gökçe, C. Akkulak, and S. Ötleş, "Predictive maintenance for industry," *International Journal of 3D Printing Technologies and Digital Industry,* vol. 3, no. 1, pp. 56–66, 2019.

[8] A. Deuter and S. Rizzo, "A critical view on PLM/ALM convergence in practice and research," *Procedia Technology,* vol. 26, pp. 405-412, 2016. https://doi.org/10.1016/j.protcy.2016.08.052

[9] W. Van der Aalst, *Process Mining: Data science in action*. Dordrecht: Springer, 2016.

[10] M. M. Sever, "Product lifecycle management (PLM) model in a service industry= service lifecyle management (SLM) model," *Çankırı Karatekin Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* vol. 15, no. 2, pp. 523-539, 2024. https://doi.org/10.54558/jiss.1191683

[11] M. Paavel, K. Karjust, and J. Majak, "PLM maturity model development and implementation in SME," *Procedia CIRP,* vol. 63, pp. 651-657, 2017. https://doi.org/10.1016/j.procir.2017.03.144

[12] T. D. Dabade, "Information technology infrastructure library (ITIL)," in *Proceedings of the 4th National Conference; INDIA Com, Computing For Nation Development*, 2010.

[13] T. R. Soomro and M. Hesson, "Supporting best practices and standards for information technology infrastructure library," *Journal of Computer Science,* vol. 8, no. 2, pp. 272-276, 2012.

[14] J. Stewart and S. Taylor, *The official introduction to the ITIL service lifecycle*. London: The Stationery Office, 2010.

[15] M. Basham, *ITIL, 4 edition*. United Kingdom: The Stationery Office, 2019.

[16] M. M. Sever, "The relations between digitalization, service innovation and service value creation capability: A model adaption in the service industry," *Verimlilik Dergisi,* vol. 58, no. 1, pp. 61-72, 2024. https://doi.org/10.51551/verimlilik.1315205

[17] M. Freitag and S. Wiesner, "Smart service lifecycle management," *Industrie 4.0 Management,* vol. 35, no. 5, pp. 35-39, 2019. https://doi.org/10.30844/I40M_19-5_S35-39

[18] L. Wang, Z. Liu, A. Liu, and F. Tao, "Artificial intelligence in product lifecycle management," *The International Journal of Advanced Manufacturing Technology,* vol. 114, no. 3, pp. 771-796, 2021. https://doi.org/10.1007/s00170-021-06882-1