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Effect Of Machine Intelligence on Service-Dominant Logic Aligned Customer Engagement and Service Design: Insights and Future Research Directions

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KEYWORDS

Artificial Intelligence, Machine Learning, Virtual Reality, Augmented Reality, Service-Dominant Logic, Customer Engagement, Service Design.

ABSTRACT

In recent years, scholars have explored Service-Dominant Logic (S-D Logic) aligned with customer engagement (CE) by providing insights into how these topics are connected, used, and deep-dive into the related concepts, including the context and application of artificial intelligence (AI), machine learning (ML), virtual reality (VR), and augmented reality (AR). Correspondingly, it has been shown to yield enhanced customer acquisition, service, and renewal, optimize service calls, and cross-sell recommendations from machine intelligence, and also conduct customer outreach. However, this body of knowledge regarding S-D Logic-aligned CE and Service Design remains siloed. Therefore, the purpose of this paper is to conceptualize and present a novel integrative framework, integrating S-D Logic-aligned CE/Service Design, and also present future research opportunities. *AI, AR, and VR will be referred to as machine intelligence (MI), in this paper, unless otherwise specified.*

1. INTRODUCTION

OpenAI ChatGPT (Generative Pre-trained Transformer) would change our lives (Bove, 2023; Olinga, 2022). Scholars agree that Artificial Intelligence (AI) is now all-pervasive (Ming, *et al.*, 2018). AI transforms consumers' experiences (James, *et al.*, 2023). New-age companies are now implementing artificial intelligence (AI) to drive customer interactions (Ruyter *et al.*, 2020; Silva and Bonetti, 2021). Chatbots are implemented in customer service (Per, 2019). Electronic Word of Mouth e-WOM (Jaylan *et al.*, 2018). Machines that use AI to mimic intelligent human behavior (Eunyoung, *et al.*, 2021). Feeling AI, e.g., a chatbot is used to engage with customers, including understanding customer emotions and feelings (Huang, *et al.*, 2021). Augmented Reality (AR) allows customers to "touch and feel" (Heller, *et al.*, 2020). Personalized digital marketing improves customer engagement (Behera, *et al.*, 2019). AR places a digital item like a household product (e.g., television) into your drawing room. Consumers can interact with products using Virtual Reality (VR) (Boyd, *et al.*, 2018). AR-enabled service augmentation (Bonnin, *et al.*, 2019). Artificial intelligence provides capabilities to process large information and data related to marketing activities (Rodrigo, *et al.*, 2021). From a market perspective, AI could add a whopping $4.4 trillion to the global economy (McKinsey, Apr 2023). 50% of work could be performed by AI by 2030 with almost all work automated within the next 40 years. "*We don't want to be left behind again, but we aren't sure how to think about AI.*" This is the sentiment shared by many global executives. (McKinsey, Sep 2023). Leaders need to build a compelling narrative for the use of AI. Identify applications and embark on value-creating-journey. From a journey perspective, there is a need to develop alternative AI-based system designs. In developing these AI-based system designs and service ecosystems, a deeper study and blueprinting are required for future and improved use cases, including research topics (Lee, *et al.*, 2022). Here lies the motivation for this research. *How to design services that drive customer engagement, in the context of artificial intelligence.* Despite the scholarly contributions, current research on the impact of machine intelligence (an umbrella term for AI, VR, and AR) on, specifically, customer engagement is siloed (See Table 1). As we notice (Table 1), there are multiple scholarly works, within the context of machine intelligence, addressing in siloes, the three foundational processes of customer engagement and three customer engagement benefits (Hollebeek, *et al.* 2019), as we shall see in the subsequent section. How do customers invest their resources (e.g., time, effort, money) in interacting with brands and products (Gao, *et al.*, 2022)? How do customers seek information and learn about a brand and product (Rahman, *et al.*, 2023)? How do customers build brand and product knowledge (Verma, *et al.*, 2021)? How do customers co-create value (Elmashhara, *et al.*, 2023)? How do customers interact with brands and products to build knowledge, to benefit themselves and others (Barari, *et al.*, 2020)? How do customers share knowledge with other actors (Vlacic, *et al.*, 2021)? From the perspective of designing services enabled by machine intelligence, these scholarly works (Table 1) also investigate, in silo, the four key building blocks of service design (Josina, *et al.*, 2020), as we shall see in the subsequent section. The *purpose* of integrating machine intelligence into the brand and product of study (Hollebeek, *et al.*, 2021). How machine intelligence is the *design material* to drive brand and product interactions with consumers (Dwivedi, *et al.*, 2019)? The key consumer touchpoints or focus *processes* that are addressed by machine intelligence (Moriuchi, *et al.*, 2020). And the *actors* that are impacted by machine intelligence-enabled products and brands (Lim, *et al.*, 2022). One of the reasons for the siloed scholarly works in studying the effect of machine intelligence on customer engagement is the notable extant research on Customer Engagement (CE). The extant research itself is largely based on siloed topics in customer engagement. However, the conceptualization of the Service-Dominant (S-D) logic (Vargo and Lusch, 2004) – informed customer engagement, integrative framework (Hollebeek, *et al.* 2019), helped establish a generalizable insight into Customer Engagement. The integrative framework comprises three customer engagement processes viz. customer knowledge sharing, customer resource integration, and customer learning. The intersection of these processes results in customer engagement-related benefits viz. customer individual operant resource development, customer interpersonal operant resource development, and co-creation. The framework has helped research crystallize and integrate the various theoretical constructs in CE/S-D logic research. This framework has improved our understanding of CE's relationships. Setting ground for the systematic investigation of the identified gap in how machine intelligence impacts customer engagement. Secondly, addressing the designing of services, products that consumers buy, and use are platforms or appliances that assist in providing benefits (Vargo and Lusch, 2004); therefore, products are best viewed as carriers of services for higher-order needs, and as enablers of customer satisfaction. Therefore, S-D Logic propagates that organizations (including manufacturers of products) compete through services. The innovativeness of these organizations is not in what they produce or manufacture but in how their products can serve customers better. There is hardly any evidence of scholarly work on how organizations can create a service design (Josina Vink, *et al.*, 2020) that is aligned with S-D logic and S-D logic-informed customer engagement. It must also be noted that Customer Engagement is context-specific (Brodie *et al.*, 2011). Therefore, the following two research objectives will be studied within the context of machine intelligence. The study will be limited to the foundational processes of Customer Resource Integration and Customer Learning, and their intersection leading to the benefit of Customer Individual Operant Resource Development. This limitation is only to simplify and demonstrate the proposed systematic approach

Table 1:

Author(s)	**Background of study**	**Customer Engagement (and service design) context**
Li Gao, *et al.*, 2022	How AI service robots have enhanced and affected customer engagement.	• The customer investing their resources (e.g., time, efforts) to engage. • Actors including machine intelligence (MI) in customer engagement.
Muhammad Sabbir Rahman, *et al.*, 2023	Customers are able to interact with pictures of products and have a 'touch and feel' experience of products and brands using AI assistance.	• Customer learning the product and brand.

		• Customer building product and brand knowledge. • Processes designed in machine intelligence (MI)
Sanjeev Verma, *et al.*, 2021	AI-driven customer acquisition, service, retention, and support. AI-driven customer insights for product improvement and marketing.	• The customer investing their resources (e.g., time, efforts) to engage. • Customer building product and brand knowledge. • The MI's purpose is to enhance customer experience and generate insights.

Table 1 (continued):

Author(s)	**Background of study**	**Customer Engagement (and service design) context**
Linda D. Hollebeek, *et al.*, 2021	AI can emulate human CRM agents while interacting with customers.	• The customer investing their resources (e.g., time, efforts) to engage. • Customer sharing information • Machine intelligence designed to emulate humans.
Maher Georges Elmashhara, *et al.*, 2023	AI-driven gamification of customer engagement in helping customers in pre-purchase interactions with the product or brand.	• Customer co-creation • Customer growth in product and brand knowledge • The customer investing their resources (e.g., time, efforts) to engage. • Actors including machine intelligence in customer engagement. Gamification as material to engage.
Catherine Prentice, *et al.*, 2023	AI allows brands to gain deeper insights into what drives customer engagement and customer outcomes.	• The consequences of customer engagement (e.g., well-being)

		• Moderating effects of MI

Table 1 (continued):

Author(s)	**Background of study**	**Customer Engagement (and service design) context**
Weng Marc Lim, *et al.*, 2022	Machine intelligence assists in understanding and driving customer experience, in the context of e-commerce. A deeper understanding, enabled by MI, helps improve customer engagement and convert customer interactions to business.	• Customer engagement themes • Purpose(s) of MI • Actors impacted by MI
Mojtaba Barari, *et al.*, 2020	Personalization of customer engagement is effective in cultures where individualism, gender equality and risk-taking are inherent.	• Customers invest their resources (e.g., time, efforts) to benefit themselves and others. • Effectiveness of machine intelligence (MI)
Aline F.S. Borges, *et al.*, 2020	Digital marketing is enhanced using AI technologies, driving customer engagement and experience.	• The customer investing their resources (e.g., time, efforts) to engage. • Customer building product and brand knowledge. • The MI's purpose is to enhance customer experience and generate insights.

Table 1 (continued):

Author(s)	**Background of study**	**Customer Engagement (and service design) context**

Marcello M. Mariani, *et al.*, 2023	AI enables robust analytics and proactively developing solutions to customer problems. Based on analytics, brands can identify and acquire new customers; and drive new value propositions.	• The consequences of customer engagement (e.g., innovation) • Moderating effects of MI
Yogesh K. Dwivedi, *et al.*, 2019	Human-centric AI is an effective way of engaging with customers, without completely relying on AI alone. AI may be considered as one of the actors in customer engagement.	• Customer co-creation • Customer resource integration to benefit themselves and others. • Value-in-use and co-creation purpose of MI
Sanjit K. Roy, *et al.*, 2023	AI empowers customers to have better control over their brand-related interactions, thereby positively engaging them.	• Customer resource integration. • Adoption purpose of MI

Table 1 (continued):

Emi Moriuchi, *et al.*, 2020	Self-service made available digitally to customers, improves customer engagement as they have access to information, CRM processes, and product information at the click of a button.	• Customer resource integration and development of product and brand knowledge • Processes of MI
Bozidar Vlacic, *et al.*, 2021	AI provides easy access to brand and product information, improving customer understanding. This enhancement of brand and product knowledge drives customer engagement in pre-purchase, purchase, and post-purchase scenarios.	• Customer growth in brand and product knowledge for self and others • Customer knowledge sharing

Thus, the two research objectives are formulated:

RO1: *Develop a novel integrative framework, integrating S-D Logic-informed CE/Service Design*

RO2: *Develop propositions for future research, in marketing for scholars, using a systematic approach proposed by the novel integrative framework, grounded on the theory of S-D logic-informed customer engagement and S-D logic-aligned service ecosystem design framework.*

Seven propositions (Propositions 1a, 1b, 1c, 1d, 2a, 2b, 3) have been developed, that were derived by analyzing the integration between CE, S-D Logic, and how it drives service design. Proposition 1a to 1d provides future research directions on how for the respective service design purpose of driving performance, ease of use, hedonic experience, and social influence, machine intelligence can affect customer resource integration (CRI). Propositions 2a and 2d provide future research directions on how for the respective service design purpose of driving customer learning and customer knowledge sharing, machine intelligence can affect customer learning (CL). Proposition 3 provides future research direction on how for the service design purpose of building customer brand and product knowledge, machine intelligence can affect customer individual operant resource development (CIORD). Section 2 provides the background for this research viz. customer resource integration, customer learning, and customer individual operant resource development within the context of machine intelligence. The fourth section introduces the S-D logic-aligned service ecosystem design framework (Vink, *et al.*, 2020) and the four building blocks of this framework. Section 3 illustrates the bibliometric research methodology adopted for the study. Section 4 shares the data analysis using performance analysis, science mapping, and network analysis. Section 5 presents findings from the literature review. And presents the propositions as the future research directions. Section 6 presents the integrated framework and how to use it for future research. The conclusion section discusses the limitations of this research.

2. LITERATURE REVIEW

This section introduces the two foundational processes of S-D logic-informed customer engagement (Hollebeek, *et al.*, 2019) areas (1) customer resource integration, (2) customer learning, and the customer engagement benefit (3) customer individual operant resource development (Hollebeek, *et al.*, 2019) within the context of machine intelligence. The final section introduces the S-D Logic-aligned service design framework (Vink, *et al.*, 2020) and the four building blocks of this framework.

2.1 Customer resource integration

Customer resource integration (CRI), one of the foundation processes from the S-D Logic-aligned CE framework (Hollebeek, *et al., 2019)*, is a customer's investment of their time, money, effort, and interaction with the brand. Customer resource integration (CRI) is the resources (e.g., time, effort, money) invested by consumers in interacting or engaging with a brand or product. Several facets enable or constrain customers to invest their resource(s) into brand interactions or engagement. *Availability*, since AI-enabled self-services are available 24/7, empowering customers with round-the-clock access to brand and product information, and support without having to wait for the service window to open or a human agent to be online. (Ameen, *et al.*, 2021). *Hedonic motivation,* Mixed Reality (MR) transforms information into engaging content for consumers (Eunyoung, *et al.*, 2021). Customer Engagement (CE) is context-specific and hence service provisioning and design are dependent on the context (Hollebeek, *et al.* 2019), for example, hedonic services. Unique and novel ways of interacting with customers are the keys to developing brand loyalty (Hasan, *et al.*, 2020). *Performance expectancy,* AI can positively influence customer-brand relationships through accurate and current information, and reliable, timely, and flexible services (Nguyen, *et al.*, 2021). *Human perception,* of AI increases their acceptance in different service situations and the everyday life of consumers (Pelau, *et al.*, 2021). *Personalization*, AI can generate and provide content that are personalized to individual customers, making the engagement relevant (Haleem, *et al.*, 2022). *Habit*, AI can incorporate behavioral insight into consumers' experiences (Puntoni, *et al.*, 2020). Over time, a consumer builds brand-related experiences and develops into varying habit levels. Different individuals can form different levels of habit (Venkatesh *et al.* 2012). Building brand and product knowledge is an outcome of past interactions (Hollebeek, *et al.* 2019). *Mediation,* customer emotions, either positive or negative emotions towards AI have an influence on customer engagement with the brand and product. (Pantano, *et al.*, 2022).

2.2 Customer Learning

Customer Learning (CL), one of the foundation processes from the S-D Logic-aligned CE framework (Hollebeek, *et al., 2019)*, is a process of unlearning and learning where the consumer builds a picture of the brand and how to understand the brand-related specifications and data, builds knowledge about the brand, including making purchase decisions. *Complexity*, if consumers considered themselves to be more capable of using an AI-enabled service, they perceived it as more useful and convenient (Lalicic, *et al.*, 2021). In essence, service design should support customer learning. *Knowledge,* product knowledge strengthens customers' product recommendations and satisfaction. Product knowledge is defined as customer learning of product information, quality, price, performance *et al.* (Masri, *et al.*, 2021). The need for information is high when customers are engaging with a brand or a product that is new (Stead, *et al.*, 2020). *Playfulness*, the more customers learn about the product and brand, the more their engagement. AI provides an environment and platform to help customers learn more, especially through gamification methods which make the learning journey interesting. (Sands, *et al.*, 2020). *Co-creation*, expanding collective knowledge enables the co-creation and sustenance of customer journeys. (Beverland, *et al.*, 2023). *Omnichannel learning*, and shopping explorations start with mobile apps in addition to other online, and offline channels. Retailers must offer more visibility and convenience of shopping. customer learning through service interactions (Timoumi, *et al.*, 2022). *Sharing*, sharing ideas on social media platforms improves the development of specific knowledge through collective strength (Chen, *et al.*, 2023).

2.3 Customer Individual Operant Resource Development (Hollebeek, et al., 2019)

Customer Individual Operant Resource Development (CIORD), one of the CE benefits from the S-D Logic-aligned CE framework (Hollebeek, *et al., 2019)*, refers to the improvement and growth in customer's brand and product knowledge and their skills to use them (Vargo and Lusch, 2008a, 2016). CIORD is the consumer's growth in brand and product knowledge.

Cognitive outcomes, AI virtual assistants can personalize and provide compelling advertising and messaging to customers that will enable recall (Ischen, *et al.*, 2022). *Hedonic experiences*, AI can drive hedonic experiences (Eunyoung, *et al.*, 2021). Positive and emotional experiences with brands can drive customers to continuously engage with them, leading to higher satisfaction (Blanca, *et al.*, 2021). CIORD is a key outcome of past interactions (Hollebeek, *et al.* 2019). AI can deliver products, even before a customer orders. *Involvement*, AI's ability to recommend the right product and solution during the purchase cycle is essential in improving customer engagement (Klaus, *et al.*, 2021). By engaging with brands and products, customers invest their time and effort (operant resources) and also build their knowledge about them (Lusch *et al.* 2010). New customers learn how to use a product and also understand the value-in-use experiences (Ramaswamy *et al.*, 2015). Existing customers further develop, or refine their brand-related resources (Hollebeek, *et al.* 2019). *Utility*, demonstration of product and brand performance drive customer behavior (Venkatesh *et al.* 2003). CIORD refers to customer's improvement in product and brand knowledge and their ability to support other customers in the ecosystem. The automotive industry has effectively adopted AI voice assistants to improve customer usability and enhance their product and brand knowledge (Burggraf, *et al.*, 2022). *Interest*, AI through gamification and continuous customer interaction creates a high level of brand and product interest within customers, improving their knowledge, and developing a positive attitude about the brand and product. (Santos, *et al.*, 2021). *Community engagement*, AI can make recommendations, encouraging customers to try out and buy new products (Wolber, *et al.*, 2021). Consumers who actively engage with products and brands, provide feedback to the producer and co-create; and also share their experience and knowledge with other customers (Sarkar, *et al.*, 2020).

2.4 S-D logic-aligned service ecosystem design framework

The S-D Logic-aligned service ecosystem design framework (Vink, *et al.*, 2020) conceptualized four building blocks that drive service design. The building blocks of (1) the *purpose* of the service design (2) The *design material* that will be used to drive the service (3) *processes* that define the service design (4) and the *actor(s)* involved in that particular service. Current research on service design, as discussed earlier is siloed, even as the scholarly works cover the four conceptual building blocks of the S-D logic-aligned service ecosystem design framework (Vink, *et al.*, 2020). *Purpose*, creating novel outcomes from resource integration and service exchange (Vargo, *et al.*, 2023). System design that may create a service system non-reproducible (and a competitive advantage) (Deacon,2006). *Design material,* gamification as an instrument to shape customers' interaction (Ciuchita, *et al.*, 2023). *Processes*, standard operating procedures, glossary, and definitions. AI helps automate the process of new product development driving customer satisfaction (Fahmy, *et al.*, 2023). Actors, like customers, invest their time and efforts with products and brands and also provide feedback, driving further engagement (Vargo, *et al.*, 2023). *Actor(s) involvement*, actors are major components of the service ecosystem, they have a more significant influence on value creation, thus impacting service design (Sakaya, *et al.*, 2022). *Actor(s) involvement*, a service design is effective if it can focus on personalization and at the same keep it relevant and practical for all actors within the ecosystem in terms of resource requirement, business processes et al (Blocker, *et al.*, 2022). With actors as major components of the service ecosystem (Sakaya, *et al.*, 2022), this paper, therefore, proposes to integrate service design with customer (actor) engagement framework (Hollebeek, *et al.*, 2019) – of *customer resource integration, customer learning and customer growth in brand knowledge*. Enable customers to be steered to specific subprocesses or touchpoints to suit their different learning needs (Danatzis, *et al.*, 2022). Customers to be effective *resource integrators* in a service ecosystem (Vargo and Lusch, 2016). Customer access to *knowledge* (product and brand knowledge) is self-directed (Ilias, *et al.*, 2022). Customers, if they have an interest in the product or brand would want to gain more information and understand them better. (Sun *et al.*, 2021).

3. Methodology

- 1242 papers from Web of Science (WoS) and 304 papers from Scopus were downloaded for literature review (Figure 1). The document information from both these platforms was downloaded as plain text. R-Studio was used for bibliometrics analysis, using biblioshiny. This study adopts a bibliometric using R programming language and Biblioshiny was used for analysis (Figure 2) (Victor, *et al.,* 2023).

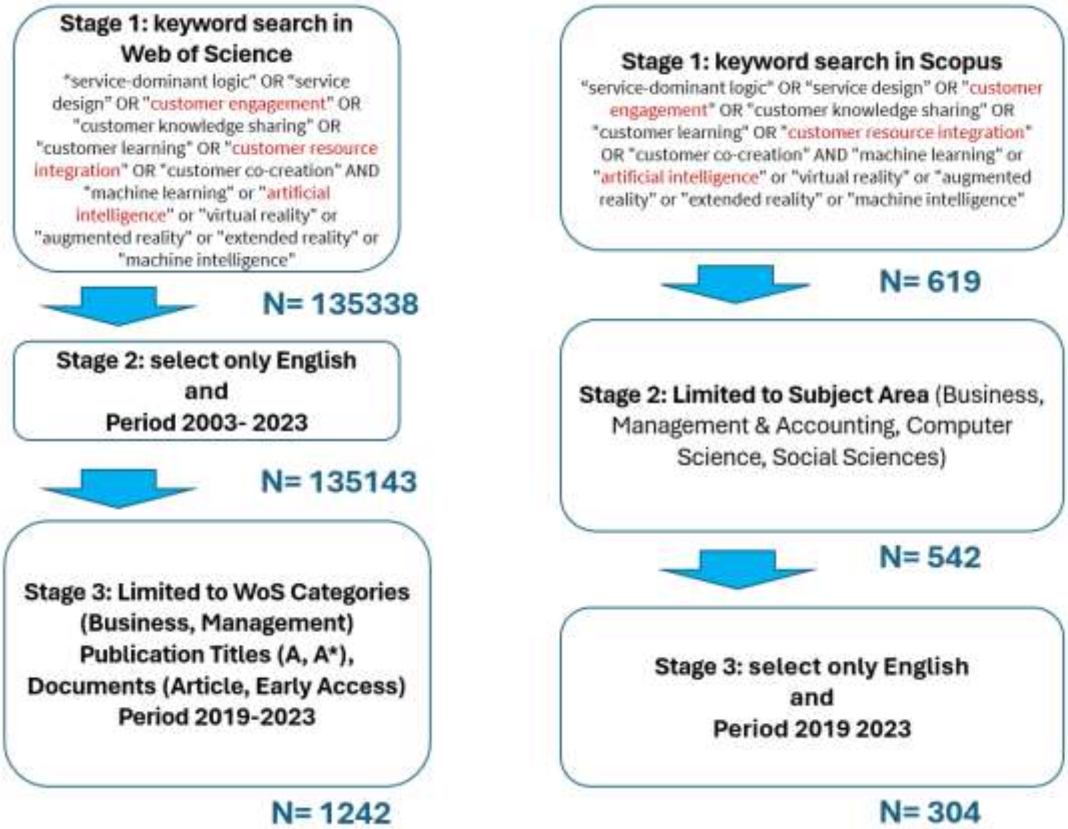

Figure 1: Download of literature from the Web of Science and Scopus

This methodology provides multiple analyses of country-wise, and author-wise, trends, themes, how authors work with others, the various sources and references, keywords used, and words that occur most in these papers. (Verma, *et al.*, 2020).

Bibliometric analysis provides the ability to understand a large volume of papers and their related data to deeply analyze trends, themes, and how the research has evolved and the future research directions (Kraus *et al.*, 2022).

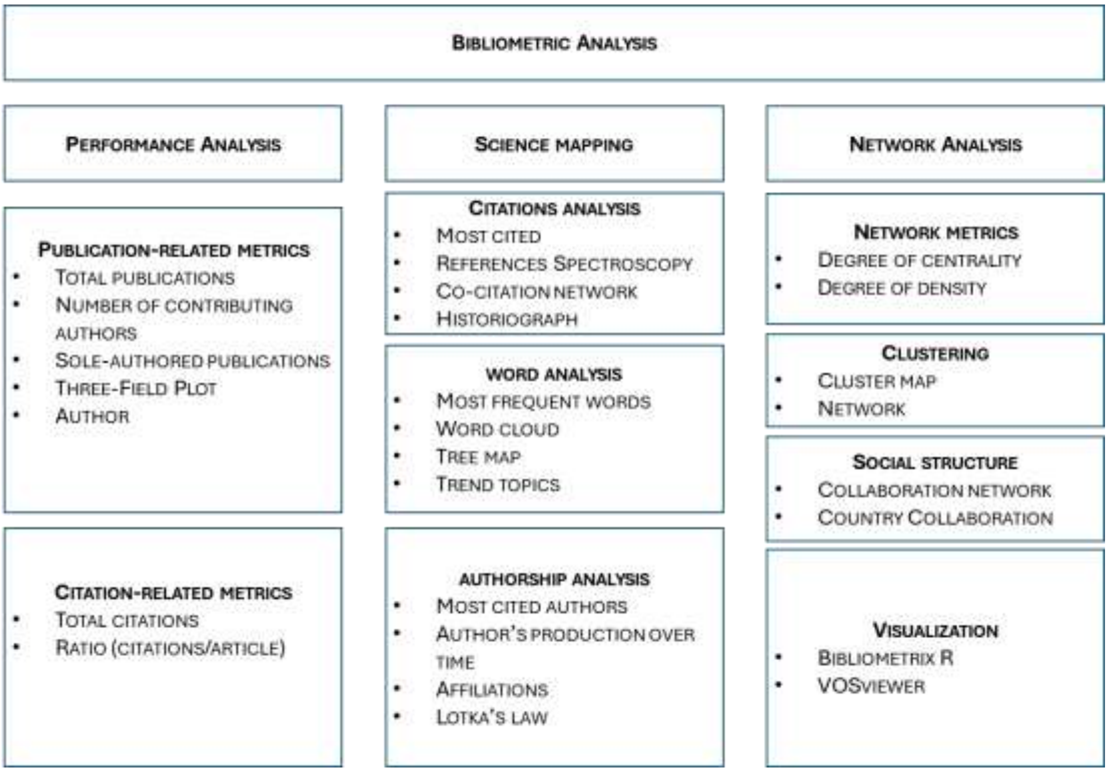

Figure 2: Bibliometric analysis methodology

Performance Analysis evaluates the literature's performance using a variety of metrics and measures including total publications and their production over time the years of study, country-wise production of articles, and single versus multi-authored publications. The review of WoS gave a CAGR of 27%, with article production of 141 in 2019, growing to 365 in 20223. 38% for Scopus, with 97 articles produced in 2023. The performance also reviews the total citations – mean citations per article each year on Web of Science, 62.17 in 2019, and 45.26 in 2020. On Scopus, 22.44 in 2019, and 21.55 in 2020. The Three Field Plot uses the 'Source-Author-Keywords' fields to analyze literature from the Web of Science and Scopus, focusing on the top 10 for WoS and 20 for Scopus, authors. The data was also analyzed for the source dynamics, focusing on the top 20 sources, and the top 20 most relevant sources. Bradford's Law of scattering or distribution method is used to analyze how the articles on the subject are scattered throughout the mass of periodicals. Science analyses the trends and themes to understand the topics covered in the literature (Weng and Satish, 2023). Corresponding author's countries' view gives insights into, country-wise, articles that have multi-authors and those that have single-authors. Author productivity is measured using Lotka's Law, to know how many of them write a certain number of articles. Word analysis includes methods like most frequent words, word cloud, and trend topics. Keyword analysis shows the grouping of keywords based on their appearance and usage in literature. Citation-related metrics include the most cited articles in the period of study 2019-2023. Global and Local citations are analyzed. Global citations count the number of citations that an article has received from all the papers within WoS or Scopus. Local citations count the number of citations from papers within the dataset (1546 in this study). The knowledge areas, within the dataset, are clubbed together as part of Co-citation analysis and bibliographic coupling. Network analysis provides insights into the authors, the countries and academia within the dataset (Naveen, *et al.*, 2021). Clustering by coupling, technique is used to study the clustering of documents based on the author's keywords and local citation. The analysis plots density against centrality. Density provides an insight into the keywords and how strong they are. Centrality provides insight into how the various themes and their associated networks interact. (Rojas *et al*., 2022). Four themes are plotted: motor, emerging or declining, niche, and basic transversal. Another method used to analyze clustering was the application of the Leiden method. It allows you to group research areas together and shows how they are related, thereby allowing us to identify the various sub-groups of topics (Traag *et al*., 2019).

4. Data Analysis

To generate the data set (Table 2a and 2b), the keywords used included the three foundational processes and benefits of S-D logic-informed customer engagement (Hollebeek, *et al.*, 2019). The context of machine intelligence. Which resulted in 1,35,338 papers on Web of Science, and 619 papers on Scopus. The publication period was limited to 2019-2023. And limited to high-quality journals. 1242 papers were finally downloaded from the Web of Science, and 304 from Scopus (Table 2).

4.2 Performance Analysis

The 1242 papers from Web of Science were from 31 sources, and authored/co-authored by 3052 authors, out of which 71 were single-authored papers. An average citation per paper of 27. Total references of 65,743. Similarly, in Scopus, the 304 papers were sourced from 226 sources, and authored/ co-authored by 844 authors. Of which 37 papers were single-authored. Average citation per paper of 11.63%. Referenced from 15499 papers.

Table 2a: Overview of data set from WoS

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Timespan	2019:2024
Sources (Journals, Books, etc)	31
Documents	1242
Annual Growth Rate %	-39.96
Document Average Age	1.55
Average citations per doc	27
References	65743
DOCUMENT CONTENTS	
Keywords Plus (ID)	2253
Author's Keywords (DE)	3719
AUTHORS	
Authors	3052
Authors of single-authored docs	71
AUTHORS COLLABORATION	
Single-authored docs	78
Co-Authors per Doc	3.3
International co-authorships %	50.16
DOCUMENT TYPES	
article	1123
article; early access	101
article; proceedings paper	10
review; early access	8

Table 2b: Overview of data set from Scopus

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Timespan	2019:2023
Sources (Journals, Books, etc)	226
Documents	304
Annual Growth Rate %	37.67
Document Average Age	1.41
Average citations per doc	11.63
References	15499
DOCUMENT CONTENTS	
Keywords Plus (ID)	1154
Author's Keywords (DE)	1032
AUTHORS	
Authors	844
Authors of single-authored docs	37
AUTHORS COLLABORATION	
Single-authored docs	37
Co-Authors per Doc	2.97
International co-authorships %	25.99
DOCUMENT TYPES	
article	173
book	7
book chapter	33
conference paper	65
conference review	14

editorial	3
review	9

Bradford's Law of Scattering shows the Journal of Business Research and the Journal of Retailing and Consumer Services as the Core Sources, in the WoS dataset. Concerning RQ2, the Scopus database analyzed using the Three-Field plot the top 20 authors' contributions to Customer Resource Integration, engaging and retaining customers (Prentice, 2020), linking performance to CE (Printice, 2020), AR in online shopping (Alimamy, 2022), and AI-Human interactions (Barile, 2022) Customer Learning, the effect of AI on customer awareness (Flavian, 2022). Customer Interpersonal Operant Resource Development, AI-voice assistant in brand attachment and well-being (Printice, 2023), and user experience using mobile apps (Gupta, 2023). Service design, AI-enabled service chain (Prentice, 2022), AI-enabled service design in tourism (LI, 2023), AI-enabled product information (Li, 2022), AI-enabled smart service design (Li, 2022), and AI analytics for new methods (Gupta, 2022).

The Three-Field plot in Web of Science (WoS) presented Hollebeek with a significant contribution as an author. Her S-D logic-informed customer engagement framework (Hollebeek, *et al.*, 2019) provides the theoretical grounding for this research paper. This framework has been cited 489 times between 2019 and 2023. Davenport, 2020, the impact of AI is highest in industries where customer interactions are high, was cited 486 times. Flavian, 2019, cited 386 times, on AI-enabled service design, to enhance customer experience along the customer journey. The most relevant sources included: the Journal of Business Research, the Journal of Retailing and Consumer Services, the Journal of Service Management, the European Journal of Marketing, and the Journal of Service Research.

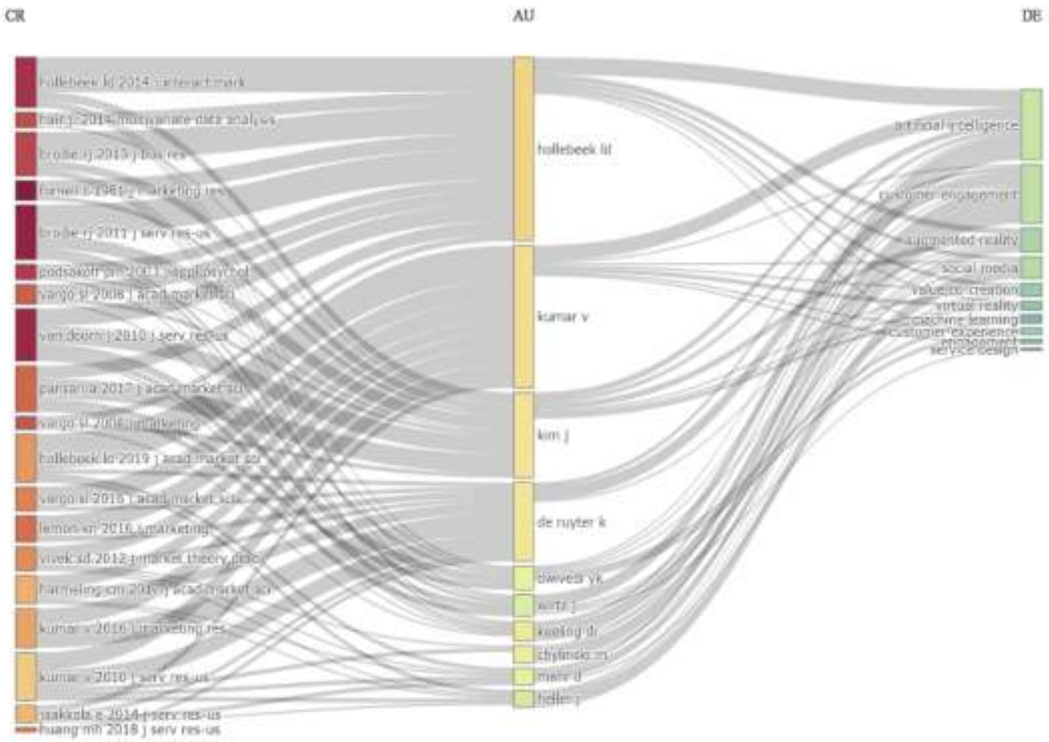

Figure 3: Three-field plot (Reference-Author-Keywords)- WoS

4.3 Science Analyses

The Corresponding author's countries' view gives insights into, country-wise articles that have multi-authors (MCP) and those that have single-authors (SCP). Scopus gives country-wise insights. The country name (MCP, SCP) data: China (8, 21), India (6, 23), the USA (10, 15), the UK (4,10), and Australia (6, 5) as the Top 5. WoS lists the USA, China, the UK, Australia, and France as the Top 5, with India at the 6th position. Using Lotka's Law to measure author productivity during the period 2019-2023, in Scopus, 5% of the authors have written at least 2 articles. Word analysis in the Scopus data set lists AI, CE, and Service design as among the 10 most frequently used words. The data set was then uploaded to VOSviewer. Of the 1032 keywords, 61 (5.9%), with a minimum threshold of occurrences of keywords to 3 were used to create the co-occurrence map (Table 3). For each of the 61 keywords, the total strength of the co-occurrence links with other keywords is calculated in VOSviewer. The keywords with the greatest total link strength are selected to create the map.

	Keyword	Occurrences	Total link strength
1	Artificial Intelligence	73	123
2	Customer Engagement	47	77
3	Augmented Reality	32	51
4	Machine Learning	32	44
5	Customer Experience	16	37
6	Virtual Reality	19	27
7	Marketing	9	25
8	Service Design	9	25
9	Social Media	8	23
10	Digital Marketing	9	21
11	Big data	6	19
12	Chatbots	7	17
13	Service-Dominant logic	11	17
14	Value co-creation	9	17
15	Customer loyalty	5	16

Table 3: Top keywords based on occurrences and link strength.

The top 15 keywords (Table 3) are listed in order of occurrences and total link strength. Machine Intelligence, Customer Engagement, and Service Design are analyzed with the highest link strength. The co-occurrence of keyword analysis in Scopus (Figure 4b) shows three color-coded clusters, using network visualization. The highest betweenness is seen for the clusters – cluster 1 (Figure 4b.1), artificial intelligence, and cluster 2 (Figure 4b.2), customer engagement. The higher the betweenness value is, the more important the node is in controlling the network connections. Cluster 1 (blue), based on association strength, associates artificial intelligence, S-D logic, and service design. Cluster 2 (green), associates customer engagement with machine intelligence (AR and VR). WoS co-occurrence of keyword analysis also presents a similarity betweenness in customer engagement and artificial intelligence (Figure 4a), using VOSviewer. The same criteria of selecting 5% keywords based on a minimum number of occurrences of a keyword to 5, was used. Machine intelligence, customer engagement, and service design were listed as the highest in terms of occurrences and total link strength. Cluster 1 (red), customer engagement. Cluster 2 (green), machine intelligence. Cluster 3 (blue) service-dominant logic.

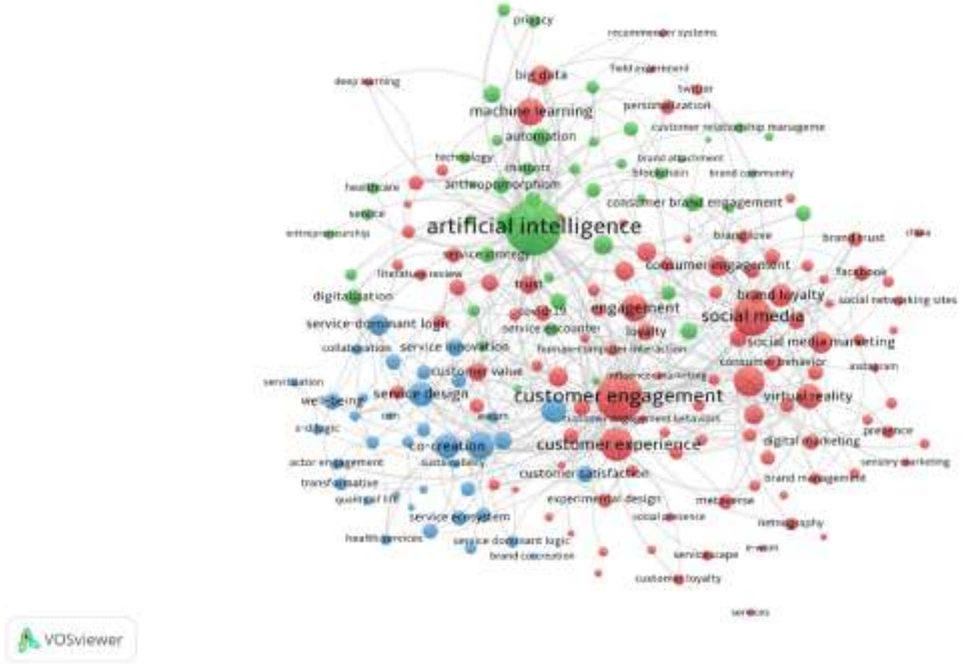

Figure 4a: Co-occurrence network of author keywords – WoS

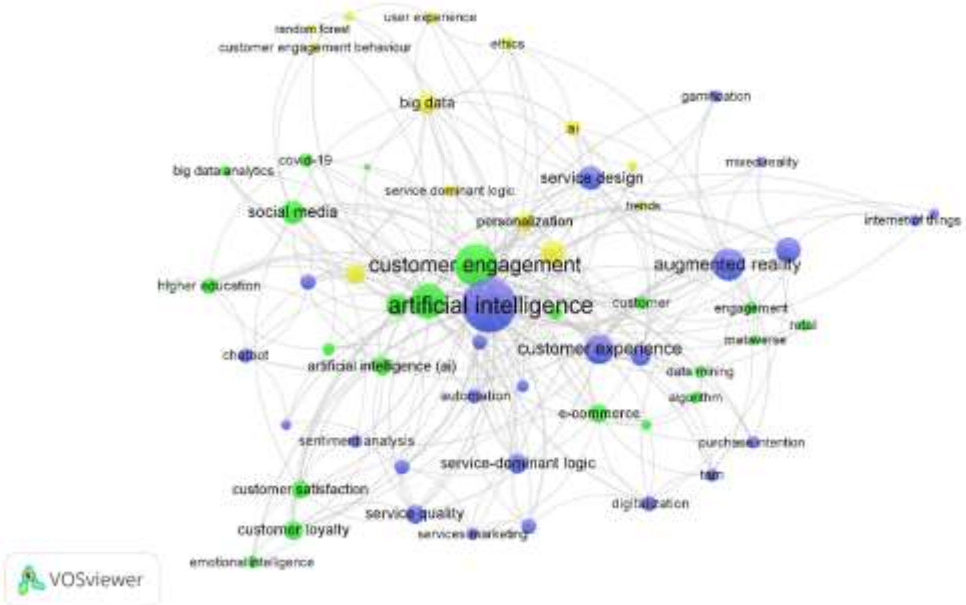

Figure 4b: Co-occurrence network of author keywords – Scopus

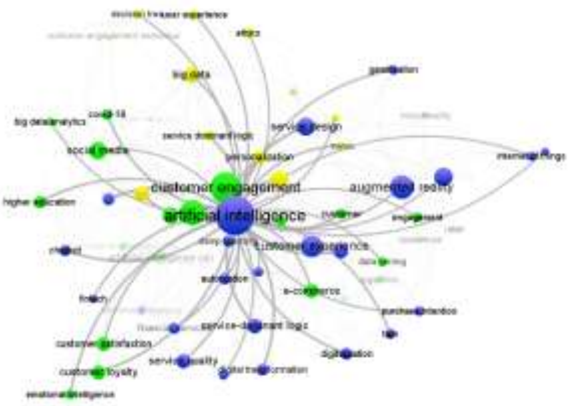

Figure 4b.1: Cluster 1

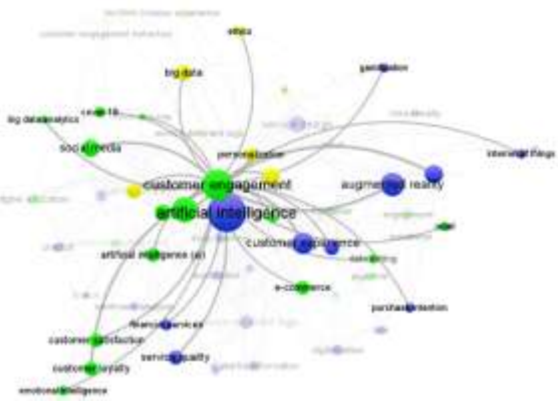

Figure 4b.2: Cluster 2

The most cited sources included the Journal of Business Research (306 WoS, 7 Scopus), Journal of Retailing and Consumer Services (169 WoS, 2 Scopus), Journal of Services Marketing (82 WoS, 3 Scopus), Journal of Service Management (78 WoS, 4 Scopus), European Journal of Marketing (70 WoS, 2 Scopus), Journal of Research In Interactive Marketing (58 WoS, 5 Scopus) and Journal of Service Research (49 WoS, 3 Scopus). The most cited countries included the USA (1319), China (641), and the UK (604). Co-citation analysis analyzes the knowledge clusters based on the cited publications. In Figure 6a, using the WoS data set, cluster 1 (red) includes authors with articles in CE, Hollebeek, 2019 with S-D logic-informed customer engagement framework, that provides theoretical grounding to this research; works on CE (Brodie, 2017; Van Doorn, 2010; Brodie, 2013; Pansari, 2017; Harmeling, 2019); brand experience (Brakus, 2009), and customer-brand relationship (Fournier, 1998). It also authors with highly cited articles on structural equation modeling, and PLS-SEM (Fornell, 1981; Hair, 2014; Henseler, 2015; Anderson, 1988). Cluster 2 (green) includes authors who provided works on machine intelligence (MI), service robots (Wirtz, 2018; Mende, 2019), AI in marketing (Davenport, 2020), and AI voice assistants (Kaplan, 2019). Cluster 3 (blue) includes authors who extended the studies on MI to understand the attributes, and acceptance, customer experience (Lemon, 2016), user acceptance, and ease-of-use (Davis, 1989), interactivity and vividness of AR (Yim, 2017) provides insights into how machine intelligence has impacted CE, augmentation of AR (Hilken, 2017), telepresence of AR (Steuer, 1992), variables influencing use of AI voice assistants (Mclean, 2019). Cluster 4 (yellow) has scholars who have given insights into S-D logic and CE. In this cluster are authors, Vargo 2004, 2008, and 2016, with their work on service-dominant logic foundational processes and axioms.

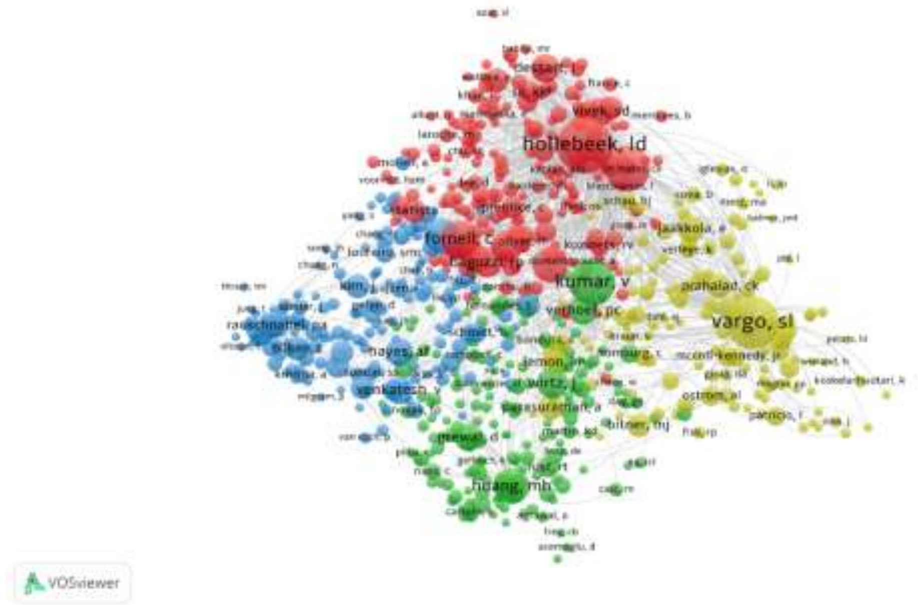

Figure 6a: Citation analysis – WoS

The citation analysis for the Scopus data set, in VOSviewer presents 3 clusters (Figure 6b). Cluster 1 (red), machine intelligence (Davenport, 2020; Haenlein, 2019; Belanche, 2019; Huang, 2018; Wirtz, 2018), and authors who provided the fundamental theoretical basis for S-D logic (Vargo, 2004, 2008, 2017). Cluster 2 (green), machine intelligence-enabled CE, (Gupta, *et al., 2023;* Wang, 2023, Wang, *et al.,* 2023; Li, *et al.,* 2021) Cluster 3 (blue), clustering with CE (Van, 2010; Brodie, 2011; Pansari, 2017; Hollebeek, 2014), customer interaction (Mclean, 2019; Javornik, 2016; Hilken, 2017).

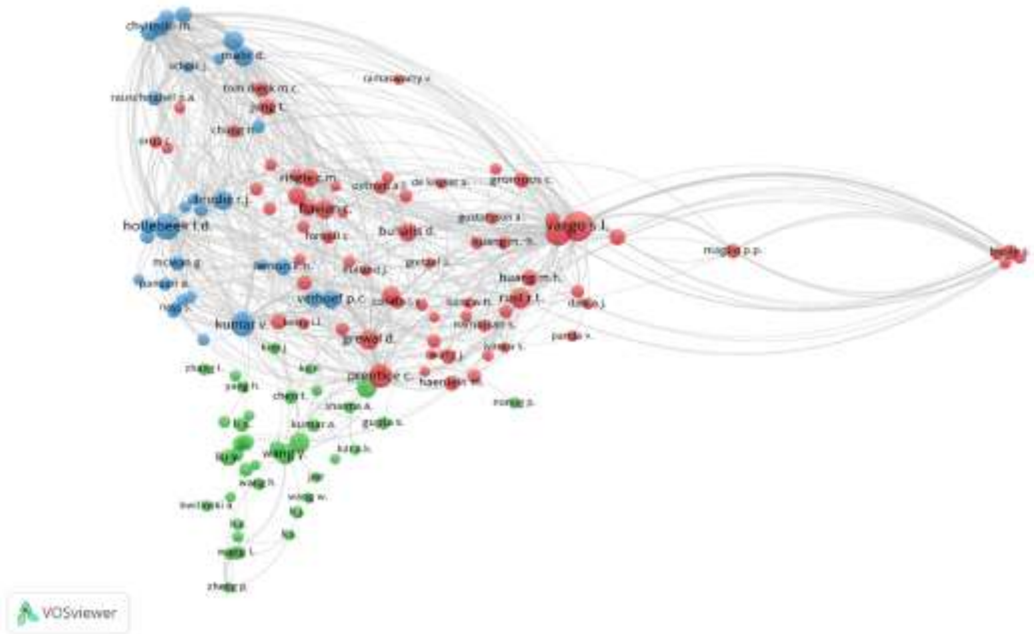

Figure 6b: Citation analysis – Scopus

4.4 Network analyses

Clustering by coupling, technique is used to study the clustering of documents based on the author's keywords and local citation (Figure 7a). Themes, using Scopus, in the section show that Motor themes are key areas of study. These include machine intelligence (McLean, *et al.*, 2019; Boletsis, *et al.,* 2020), and service design (Gushima, *et al.,* 2020; Wang, *et al.*, 2019). The themes that are comprehensive and have matured, are plotted as Niche. These include the foundational processes and benefits of S-D logic-informed customer engagement (Hollebeek, *et al.*, 2019), and services marketing. Declining themes need to be worked upon further in terms of deeper study and research. Resource integration, as identified in this paper is an area of research interest, considering there is hardly any evidence of a systematic study of customer resource integration. Technology readiness and acceptance are niche and emerging. The areas that need additional study, and are important to the study are shown as Basic. Topics like machine intelligence-enabled AI, (Rahman, *et al.,* 2023; Hossain, *et al.*, 2022), AI-enabled S-D logic, and AI-enabled service design (Kikuchi, *et al.*, 2019; Li, *et al.,* 2023) are important topics, however, require significant study.

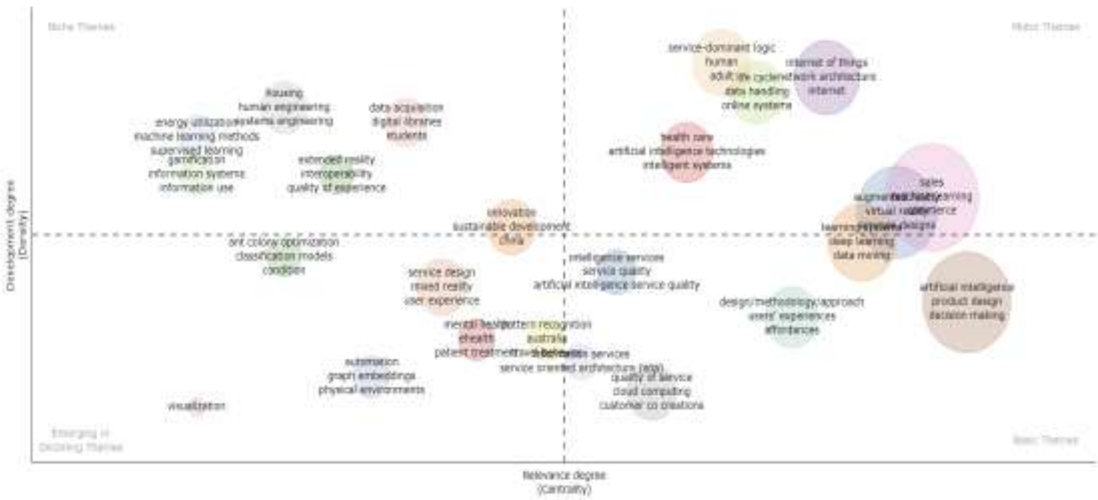

Figure 7a: Thematic Map – Scopus

Themes, using WoS, (Figure 7b) located in the Motor themes quadrant include machine intelligence and MI-enabled customer engagement articles (Davenport, 2020; Flavian, 2019; Wongkitrungrueng, 2020; Huang, 2021; Hollebeek, 2019). Service design (Kim, *et al.,* 2022; Lu, et al., 2020; Foster, 2023; Fearn and Hook, 2023; Saha, et al., 2023). The Niche and Emerging themes include the foundational processes of S-D logic-informed, MI-enabled CE (Sjodin, 2020; Longoni, 2022; Mustak, 2021), and MI-enabled service design (Ma, 2020; Makarius, 2020; Langley, 2021; Ostrom, 2021; Vargo, 2020; Vink, 2021). Basic and Emerging themes include S-D logic- informed CE (Hollebeek, *et al.,* 2019), CE in service (Kumar, 2019), value co-creation (Tajvidi, 2020), gamification and brand engagement (Xi, 2020), and customer-brand interaction (Prentice, 2019).

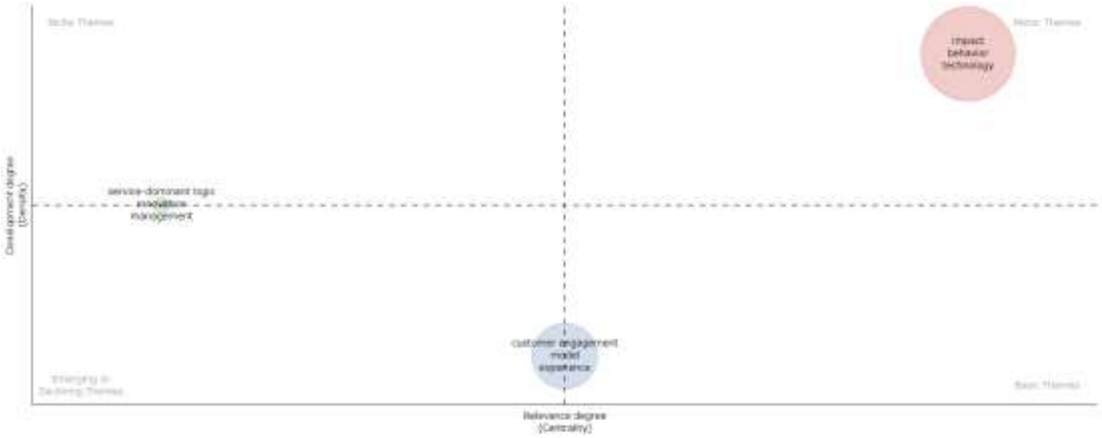

Figure 7b: Thematic Map – WoS

5 Results

The results section discusses the findings from the literature study, and presents propositions, as future research directions, based on the literature review. Seven integrated propositions service design; and S-D logic-informed Customer Engagement framework.

5.1 Key results and findings from the literature review

5.1.1 Major S-D logic-aligned CE/Service Design – publishing journals

The journal-wise number of published S-D logic-aligned CE/Service, enabled by machine intelligence articles, and the citation count are presented in Table 4. Citations provide the impact of the journal (Hollebeek, *et al.,* 2022). The corresponding values for both WoS and Scopus are tabulated. Journal of Business Research leads, both in terms of the number of articles published and also in terms of citation, with the Journal of Retailing and Consumer Services a distant second. The top 25 journals are listed in Table 4.

	Table 4: Major S-D logic-aligned CE/Service Design – publishing journals						
		WoS	**SCOPUS**			**WoS**	**SCOPUS**
	Source	**Articles**	**Articles**		**Source**	**Total Citations**	**Total Citations**
1	Journal of Business Research	146	4	1	Journal of Business Research	5637	266
2	Journal of Retailing and Consumer Services	57	2	2	Journal of Retailing and Consumer Services	1284	129
3	Journal of Service Management	41	3	3	Journal of the Academy of Marketing Science	1178	-
4	Journal of Services Marketing	41	1	4	Journal of Service Management	701	105
5	European Journal of Marketing	34	2	5	Journal of Service Research	564	174
6	Journal of Product and Brand Management	22	-	6	Journal of Interactive Marketing	455	124

7	Journal of Marketing Management	19	-	7	European Journal of Marketing	447	102
8	Journal of Service Research	18	3	8	Journal of Consumer Research	408	-
9	Journal of Research In Interactive Marketing	14	5	9	Journal of Product and Brand Management	399	-
10	Journal of the Academy of Marketing Science	12	-	10	Journal of Services Marketing	365	18
11	Journal of Brand Management	11	-	11	International Journal of Research in Marketing	322	-
12	Journal of Consumer Behavior	9	-	12	Journal of Research In Interactive Marketing	309	192
13	International Marketing Review	9	-	13	Journal of Marketing Management	268	-
14	Journal of Interactive Marketing	8	1	14	Journal of Marketing	213	-
15	International Journal of Research in Marketing	8	-	15	Journal of Brand Management	159	-
16	Journal of Information Technology	8	-	16	Journal of Information Technology	81	-
17	Asia Pacific Journal of Marketing and Logistics	8	-	17	Asia Pacific Journal of Marketing and Logistics	77	-
18	Journal of Innovation and Knowledge	6	-	18	Journal of Marketing Research	75	-
19	Journal of International Marketing	6	-	19	Journal of Fashion Marketing and Management	71	-
20	Creativity and Innovation Management	5	-	20	Journal of Consumer Behavior	64	-
21	Journal of Management Information Systems	5	-	21	Creativity and Innovation Management	58	-
22	Journal of Fashion Marketing and Management	4	-	22	International Journal of Advertising	54	-

23	International Journal of Advertising	4	-	23	Journal of Advertising	53	-
24	Journal of Advertising	3	-	24	International Marketing Review	51	-
25	Journal of Retailing	3	-	25	Journal of Retailing	40	-

5.1.4 Major S-D logic-aligned CE/Service Design themes

Citation analysis on the Scopus data set (Figure 6b), visualizes three clusters – cluster 1 (Figure 8a), cluster 2 (Figure 8b), and cluster 3 (Figure 8c) using VOSviewer. The knowledge areas are grouped based on the analysis of publications that are cited. Table 7 studies the four themes (clusters) and presents sample articles that build each cluster within Figures 8a, 8b, and 8c.

Table 7: S-D logic-aligned CE/Service Design themes (clusters) and sample articles

Cluster 1 (Figure 8a)*, machine intelligence and S-D logic*

Definitions, use cases and impact of AI (Siri) (Kaplan and Michael, 2019)

Robots in the service industry (Wirtz, *et al.,* 2018)

AI in marketing (Davenport, *et al.,* 2020)

S-D logic (Vargo, 2004, 2008, 2017).

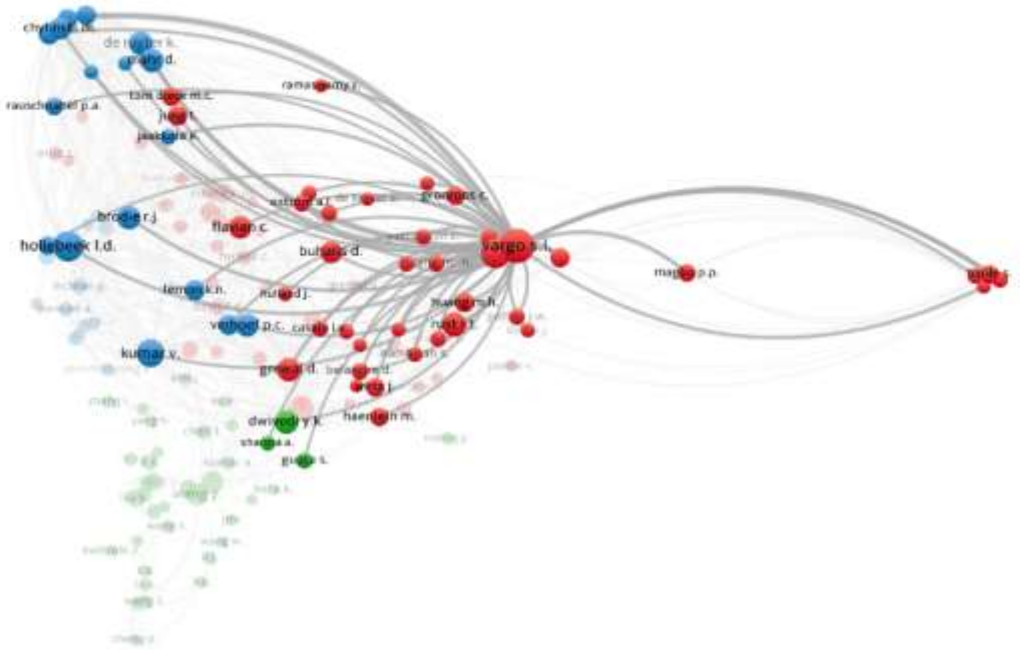

Figure 8a: Cluster 1

Cluster 2 (Figure 8b)*, MI-enabled CE*

Customer experiences in the era of AI. (Gupta, *et al.*, 2023)

Value co-creation within the supply chain, in B2B scenario, using AI (Li, *et al., 2021)*

Customer engagement on social media (Wang, 2023)

Services robots in customer service (Wang, et al, 2023)

Cluster 3 (Figure 8c)*, Customer engagement.*

Consumer engagement in a digital community (Brodie, *et al.,* 2011)

Customer Engagement: Conceptual Domain, Fundamental Propositions, and

Implications for Research (Brodie, *et al.,* 2011)

Customer Engagement Behavior (Doorn, *et al.,* 2010)

S-D logic-aligned customer engagement (Hollebeek, *et al.,* 2019)

Customer engagement and relationships of processes and benefits (Pansari and Kumar, 2017)

Understanding Customer Experience Throughout the Customer Journey (Lemon, *et al.,* 2016)

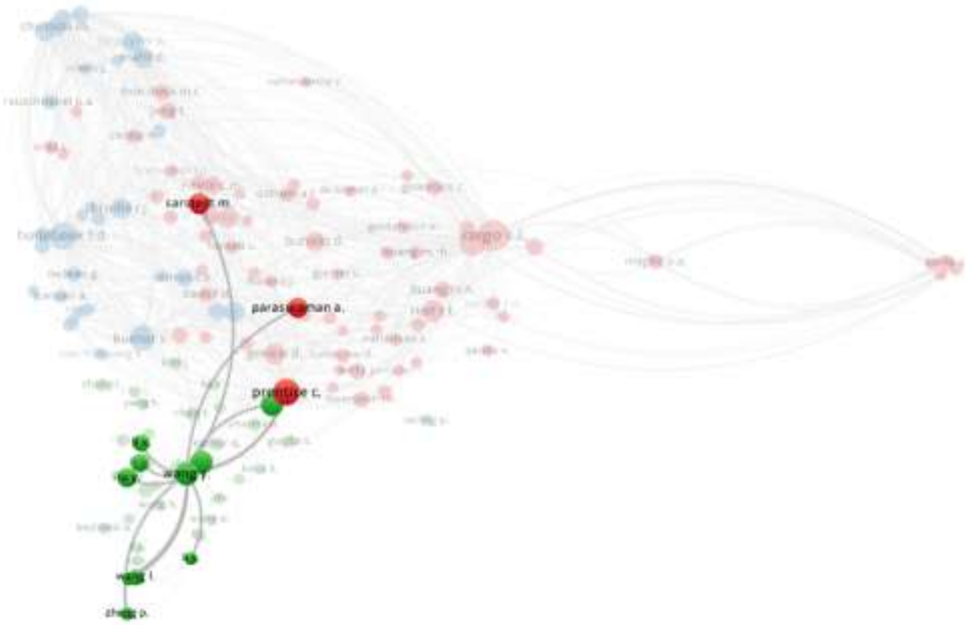

Figure 8b: Cluster 2

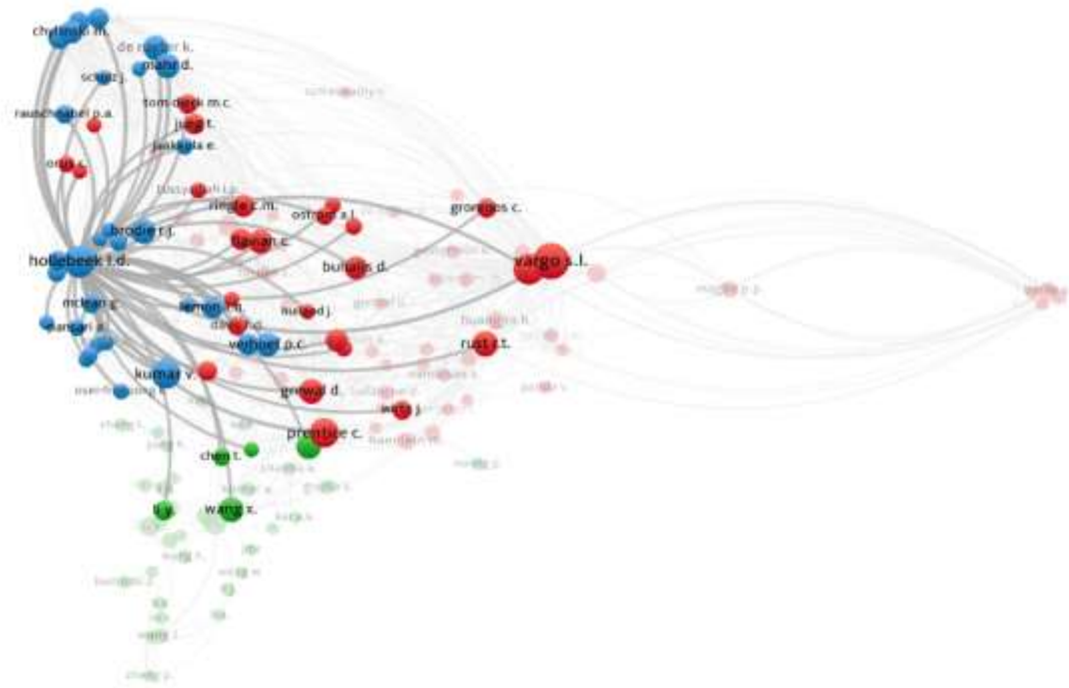

Figure 8c: Cluster 3

5.2 Propositions for Future Research Directions

5.2.1 Service Design for Customer Resource Integration

Customer resource integration refers to the investment of a customer's time, efforts, money, knowledge, and skills to help and support other customers, and actors. Utility, namely *performance expectancy*, how brand and product performance is effective I driving customer response and intent (Venkatesh *et al.* 2003). *Performance* impacts the ethical perceptions of AI, which in turn influences trust in using AI (Maria *et al.*, 2022). Driving customers to invest their resources (customer resource integration- CRI) (e.g., time, effort, money) in interacting with brands and products. Scholarly works have demonstrated empirically that easy to use or less *effort* is a driver of customers using AI devices (Cao, *et al.*, 2021). Consumers invest their time, money, and effort in interacting with the brand and in effect learn about the brand. This investment (operant resource) helps build knowledge and skills to engage and use the brand. (Lusch *et al.* 2010). New customers learn how to use a product and also understand the value-in-use experiences (Ramaswamy *et al.*, 2015). Existing customers further develop, or refine their brand-related resources (Hollebeek, *et al.* 2019). In essence, it helps customers reduce their effort (CRI) in using AI. *Social influence* is a key driver in enabling co-creation through AI (Solakis, *et al.*, 2021). In collectivistic cultures (product) one-to-one customer interaction and also interaction with the larger group drives CE (CRI) (Dhruv *et al.*, 2020). Women and men demonstrate different ways of deciding on technology use (Venkatesh *et al.* 2000). Therefore, customer resource integration may vary with gender. AI voice assistants are found in a wide range of devices like mobile phones, televisions *et al.* Voice assistants as a human-computer interaction enable users to interact with technologies using their voice to invoke spoken commands (Humphry, *et al.*, 2020). *Situation factors* e.g. resource availability shape customers' willingness to invest time and effort (CRI) in AI (voice assistant-enabled devices) (Hollebeek, *et al.* 2019). Individuals interact with AI-enabled smart devices for *hedonic* benefits which accelerate their use and adoption of such devices (Aiolfi, 2023) and (Venkatesh *et al.* 2012).

Proposition 1a: *If performance is one of the value propositions (purpose) of a brand and product, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer resource integration. Through the design of service processes for engagement with actors involved. (E.g., Mobile Augmented Reality apps act as a stimulus to influence consumer experiences and performance (Qin, et al., 2020))*

Proposition 1b: *If ease-of-use is one of the value propositions (purpose) of a brand and product, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer resource integration. Through the design of service processes for engagement with actors involved. (E.g., AR wearables have the potential to make certain customer activities, e.g., information seeking easy to use (Holdack, et al., 2019))*

Proposition 1c: *If hedonic experience is one of the value propositions (purpose) of a brand and product, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer resource integration. Through the design of service processes for engagement with actors involved. (E.g., Technologies like augmented reality applications provide hedonic services (Markus et al., 2019))*

Proposition 1d: *If gender-specific differentiation is one of the value propositions (purpose) of a brand and product, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer resource integration. Through the design of service processes for engagement with actors involved (E.g., Different consumers may differ in their purchase intent of environmentally sustainable products, enabled by AI, and vary by gender) (Frank, 2021))*

5.2.2 Service Design for Customer Learning

Customer Learning is a continuous process of gaining knowledge and information about a brand and product and developing deeper insights. This continuous process develops into changes in customer behavior towards the product and brand (Mena and Chabowski 2015; Payne *et al.* 2008, p. 86; Sinkula *et al.* 1997). Cognitive engagement on the other hand deals with how customers interact with AI devices, impacting their involvement with it (Dwivedi, *et al.*, 2021). Consumers who develop an interest in a brand or product, try to understand them better and are motivated to do so (Gilal *et al.*, 2019; Ryan and Deci, 2000b). And the process of learning becomes enjoyable. (Sun *et al.*, 2021). Consumers share their experience and knowledge about the brand and product on social platforms, even if their experience and skills are limited, simply to show their identification with such brands and products (e.g., an iPhone) (Hamilton, *et al.*, 2021). In these cases, other people also influence and motivate you to engage with the brand and product (Ryan and Deci, 2000b). Customers share information about the brand and product to help others (Bock *et al.*, 2005; Chen *et al.*, 2009).

Proposition 2a: *If providing an environment for customers to enjoy learning about the brand and product, is the key purpose of your service design then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer learning. Through the design of service processes for engagement with actors involved. (E.g., Gamification has direct effects on user engagement in e-commerce (Alejandro, et al., 2021))*

Proposition 2b: *If customer knowledge sharing is the key purpose of your service design, to drive customer learning, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer learning. Through the design of service processes for engagement with actors involved. (E.g., Sharing of knowledge in online health communities (Meng, et al., 2021))*

5.2.3 Service Design for Customer Individual Operant Resource Development

Customer Individual Operant Resource Development (CIORD) is the investment of the customer's knowledge and skills to improve his understanding of the brand and product thereby driving CE. (Vargo and Lusch 2008a, 2016). Customers invest their time, money, and efforts to engage with the brand and product and learn continuously. This leads to their growth in brand and product knowledge through this investment (operant resource) Hollebeek, *et al.* 2019). AI empowers and generates information and knowledge on new marketing activities, customer insights, and the ecosystem (Varsha, *et al.*, 2021). AI provides insights on products, places, prices, and promotions, at the click of a button using big data (Bag, *et al.*, 2020). Personalized knowledge provides one-to-one information to individual customers based on their needs (Rhem, 2021). Using social media tools to increase brand awareness and reach new potential customers (Obermayer, *et al.*, 2022).

Proposition 3: *If growing customer brand and product knowledge is the key purpose of your service design, then there is a need to study how machine intelligence can be integrated as an operant resource to drive customer individual operant resource development. Through the design of service processes for engagement with actors involved. (E.g., AI-based recommender systems in fashion that provide personalized product knowledge) (Mohammadi, et al., 2021))*

6 Discussion, implications, and limitations

The seven propositions presented in the previous section are mapped in Table 8. The integrative framework presents a systematic method of identifying and investigating areas for future research. Unlike current research, that is siloed.

S-D logic-informed customer engagement (Hollebeek, *et al.*, 2019) S-D logic-aligned service ecosystem design framework (Josina Vink, *et al.*, 2020) building blocks	**Customer Resource Integration**	**Customer Learning**	**Customer Individual Operant Resource Development**
Purpose	*Performance, or hedonic experience, or ease of use, or building customer brand knowledge, or enabling customer learning*		
Design Material **Processes** **Actor Involvement**	*Proposition 1a* *Proposition 1b* *Proposition 1c* *Proposition 1d*	*Proposition 2a* *Proposition 2b*	*Proposition 3*

Table 8: Integrative framework of S-D logic aligned Service Design and customer engagement.

6.1 Implications for research

Marketing scholars can now stimulate discussions, and investigations into each of the propositions to develop processes and actor involvement to achieve a particular service design. And also, empirically investigate the set processes for the specific service purpose. Unlike current research, which is siloed, academicians can now adapt this framework to enable a systematic and integrated approach to studying the impact of machine intelligence on customer engagement and service design imperatives.

Marketing scholars can extend the framework to include all three foundational processes of S-D logic-informed customer engagement and the three benefits.

6.2 Implications for practice

Practitioners can use the integrated framework to create a blueprint for product development and enhancement to meet their business objectives. As an example, the development of AI Voice Assistant (AIVA) as an operant resource to be integrated with household devices like televisions, refrigerators, microwaves, etc. To co-create value-in-use with the customer, AIVA as an operant resource may now be systematically developed as part of its product life cycle. Building performance, creating a hedonic experience, making it easy to use. Enhancing the functionality of AIVA to accelerate customer learning. Making the learning process fun, so that customer invests resources (e.g., time and effort) in using the product and brand and thereby building brand and product knowledge. Practitioners can also use this framework to design service processes for their specific value proposition and service design purpose. And design service implementation and roll-out keeping in view the actors involved in the service purpose. The framework thus provides a systematic approach to design, build, and execution; and progressive elaboration of service roll-out. Instead of a siloed and ad-hoc approach to developing and competing with operant resources.

6.3 Limitations and Conclusion

Biblioshiny and R present the analysis of academic literature on customer engagement and service design, within the context of machine intelligence. The analysis of 1546 articles produced from 2019 to 2023 featured in the Scopus and Web of Science database demonstrates the link between service-dominant logic and service design. This study presents a framework for systematically studying and identifying future research and implementation in the twin areas, integrated and not siloed, within the context of machine intelligence. Secondly, the study presents seven propositions as future research directions that stimulate academic discussion and action for practitioners. This paper is limited to studying only two S-D logic-informed customer engagement processes and one benefit. This study may be extended to cover the customer knowledge-sharing process and the two aspects of customer co-creation and customer investment in brand-engagement (operant resource). The building blocks of S-D aligned service design may also be elaborated to discuss and investigate the processes and actor involvement for a specific service purpose.

7.0 Author contributions

Joseph Dolphin: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing. **Dr. Dipanjan Kumar Dey:** Visualization, Supervision, Project administration

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