Customer Profitability and Digitalization in the B2B Market: Systematic Literature Review

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ABSTRAK

This study presents a Systematic Literature Review (SLR) to synthesise and analyse the roles, contributions, challenges, and gaps in the literature at the intersection of Customer Profitability Analysis (CPA), digitalisation, and the Business-to-Business (B2B) market. Using an SLR approach, this study identifies and evaluates 30 scholarly articles that focus on CPA in B2B markets within the context of digitalization. The analysis is conducted thematically to identify models, non-risk challenges, and integration gaps. Digitalization has transformed B2B CPA from a purely historical, backward-looking model into a predictive, risk-adjusted approach. The use of Machine Learning (ML) and data mining techniques (such as Boosting and Random Forest) has proven accurate in estimating customer churn probabilities and risk levels, which are then integrated into Customer Lifetime Value (CLV) calculations based on Risk-Adjusted Revenue (RAR). The main non-risk challenges include failures in integrating legacy systems (ERP, CRM, SCM), which hinder accurate tracing of cost-to-serve, as well as the need for managerial cultural change and the adoption of new hybrid technology roles.The key gap in the literature is the lack of empirical and technical studies that explicitly explain how digital technology platforms (hybrid actors such as chatbots or e-marketplaces) automatically capture and allocate service costs to B2B customer accounts within traditional cost accounting models, particularly Activity-Based Costing (ABC).

Keywords: Customer Profitability Analysis, Digitalization, B2B Market

INTRODUCTION

Digital transformation has radically changed the business landscape, especially within the Business-to-Business (B2B) market concept. In general, B2B companies are currently facing increasing pressure to optimize their customer relationships in response to market volatility and global competition. Data from Anan (2023) indicates that companies with superior customer analytics capabilities (which are often driven by digitalization) can achieve a profitability increase of up to 15–20% compared to their competitors. This phenomenon highlights the importance of Customer Profitability Analysis (CPA) with an approach that goes beyond total revenue to measure the costs and profitability associated with each individual customer as a key to efficient resource allocation and strategic decision-making in a digital environment.

However, the implementation of CPA in the B2B context faces unique challenges compounded by digitalization. The B2B market is characterized by a smaller number of customers, higher transaction values, and complex, long-term relationships (Purmonen et al., 2023). The main challenge is the complexity in measuring differentiated Cost-to-Serve in the digital era. Digital infrastructure generates massive volumes of data (Big Data) from various touchpoints—ranging from e-procurement platforms, automated Customer Relationship Management (CRM), to digital technical support services (Voorhees et al., 2025). The core problem that arises is how to accurately integrate, process, and model this large and varied volume of data to calculate B2B customer profitability in real-time or near real-time.

Several previous studies have examined CPA, focusing on traditional frameworks such as Activity-Based Costing (ABC) or Customer Lifetime Value (CLV) models. For example, Lau et al. (2016) reviewed the integration of ABC in CPA measurement, while Ruch & Sackmann (2012) explored the role of CLV in B2C.

Although these studies provide a strong foundation, a clear research gap is evident: the lack of a focused and in-depth synthesis on the intersection between CPA, Digitalization, and the B2B Market. The majority of existing research tends to be: (1) theoretical or conceptual without empirically integrating the implications of digital technology; (2) more focused on the B2C market where the dynamics of relationships and cost complexity differ ; or (3) only touches upon one aspect of technology (e.g., the role of CRM) without providing a comprehensive overview of the overall impact of digitalization.

Therefore, this study aims to complement the limitations of previous studies by conducting a Systematic Literature Review (SLR). By adopting a rigorous SLR methodology, this research will systematically identify, evaluate, and synthesize scholarly literature that explicitly discusses Customer Profitability Analysis (CPA) in the B2B market within the context of digitalization. This approach will allow for the identification of emerging methodological trends (e.g., the use of Machine Learning to predict B2B profitability), specific implementation challenges, and opportunities created by Big Data and analytics.

This research is expected to provide significant new contributions. Theoretically, this SLR will produce a comprehensive conceptual framework, map the evolution of this discipline in the digital era, and explicitly identify future research agenda at the intersection of these three fields. Practically, the findings of this research will provide invaluable insights for B2B managers and executives, assisting them in designing and implementing CPA systems that are more sophisticated, accurate, and relevant to a data-driven business environment. The main objective of this article is to provide a critical review and synthesis of scholarly literature on Customer Profitability Analysis in the context of the digitalization-driven B2B market, identifying the key models, challenges, and opportunities relevant to academics and practitioners. The practical benefit for the B2B sector is an improved capability in profitability-based decision-making, leading to optimized pricing, increased retention of valuable customers, and smarter allocation of sales and marketing resources.

Main Research Question: What are the roles and contributions of information technology systems (e.g., CRM, Data Analytics) in enhancing the effectiveness of Customer Profitability Analysis (CPA) in the B2B market?

- **Sub RQ 1:** What are the digital technical capabilities most frequently discussed to support CPA in B2B?
- **Sub RQ 2:** What gaps exist in the literature regarding the integration between technology platforms and traditional cost accounting models (such as ABC) in B2B CPA?
- **Sub RQ 3:** What are the main non-risk challenges in implementing CPA in a digitalized B2B environment?

Theoritical Background

Customer Profitability Analysis (CPA) and its derivative metric, Customer Lifetime Value (CLV), are essential disciplines in modern management. This concept is rooted in the understanding that customers are a fundamental source of revenue and a vital resource for corporate profitability and performance (W. Huang et al., 2024). The study of customer profitability analysis (CPA) attempts to quantify the financial value of each customer or customer segment as a basis for allocating marketing and sales resources. Traditional approaches include ABC analysis (customer classification based on sales/profit contribution), customer past value (CPV), and customer lifetime value (CLV), which calculates the historical and prospective profit contribution of customers by discounting cash flows and considering purchase frequency and relationship duration (Dawson et al., 2017).

In addition to monetary measures, modern CPA utilizes behavioral information such as recency, frequency, and monetary value (RFM) to assess customer "value" and perform segmentation to target marketing and service efforts (Ryu et al., 2025). Advanced variations of RFM add dimensions such as relationship length (LRFM), product category/type (RFMC/FRAT), or different service types, making them better able to capture the heterogeneity of profit contribution across business lines or service categories within a single B2B customer.

Digitalization and Digital Transformation (DT) refer to the integration of digital technology that transforms how companies operate, compete, and create value (Brynjolfsson & McAfee, 2014). In the B2B context, technology serves as a key driver of efficiency and competitive advantage. Technologies such as Artificial Intelligence (AI), Machine Learning (ML), Big Data Analytics, and Cloud Computing enable companies to improve decision-making and streamline operations (Liu et al., 2024). Digital Transformation is considered a process driven by capabilities. The Dynamic Capabilities (DC) framework emphasizes the need for companies to sense market changes, seize innovation opportunities, and reconfigure their resources to maintain an advantage in a dynamic digital ecosystem (Warner & Wäger, 2019)

The B2B market is characterized by complex relationships, high transaction values, and the importance of post-sales relationship management (Homburg et al., 2002). After-sales service in B2B market is a critical factor for customer satisfaction and retention. In the manufacturing context, organized after-sales service can turn costs into revenue opportunities (Voorhees et al., 2025).

METHODOLOGY

Over the last few years, the Systematic Literature Review has become an important research method due to its clear advantages over Traditional Literature Review. A Systematic Literature Review (SLR) is a research method for identifying, evaluating, and interpreting research results relevant to a specific topic, particular research, or phenomenon of concern (Kitchenham, 2004). The Systematic Literature Review is a qualitative approach that is descriptively qualitative of relevant research results. In conducting a systematic literature review, there are tools to help researchers select relevant articles such as Publish or Perish, Covidence, Zotero, and Mendeley (Watajdid et al., 2021). The guideline used for conducting the systematic literature review is the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guideline. PRISMA is a reporting guideline designed to improve the quality and transparency of reporting systematic reviews and meta-analyses. PRISMA provides a minimum list of items that should be reported in an SLR article, helping authors provide a complete picture of the methods used, why the review was conducted, and what was found (Sastypratiwi & Nyoto, 2020).

Search Phase

In this study, we use the systematic literature review method with the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines. The systematic review process is carried out in several stages:

a. Planning: Formulating specific research questions and developing a research protocol focused on customer profitability analysis and digitalization in the B2B Market, and searching for gaps and inconsistencies from previous research..

b. Literature search: We searched international databases using *Publish or Perish*. We then used several related terms to search for articles by including relevant keywords ("customer profitability" and "customer profitability analysis" and "customer life time value" and "digitalization" and "B2B Market")

c. Study Selection: 1. Articles published in 2014-2025.

2. Articles sourced from Google Scholar and Scopus.

3. Credible sources from reputable and Scopus-indexed journals.

4. Literature that does not meet these criteria or lacks empirical data is excluded from the study

d. Quality assessment: Evaluating the methodological quality and relevance of each included study.

e. Data extraction: Collecting relevant information from each study using a standard format.

Selection Phase

To filter the most relevant articles for this literature review, certain inclusion and exclusion criteria were applied to the search results. This study exclusively used articles published in scholarly journals, as they are considered to have validity as "certified knowledge". Therefore, other publication types such as conference papers, books,

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book chapters, or other formats were excluded from the analysis. Within these criteria, the publication timeframe was limited to articles published between 2014 and 2025. This time limitation was applied to ensure that only the most recent articles are analyzed, thereby maintaining the relevance of the concepts and theories discussed regarding customer profitability analysis and digitalization in the B2B market. This approach is particularly important given the rapid evolution of research in the fields of digitalization and customer profitability analysis, ensuring that the findings and recommendations remain applicable to the present time. The inclusion and exclusion criteria used in this systematic literature review are presented in Table 1.

Table 1. Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Publication Year	2014-2025	Other than 2014-2025
Language	English	Other than english
Subject Area	Customer Profitability Analysis, Digitalization, B2B Market	Not Customer Profitability Analysis, Digitalization, B2B Market
Document Type	Article	Not Article

In addition to applying the inclusion and exclusion criteria, this research applied a quality assessment framework to ensure the relevance and credibility of the sources used. This assessment was based on three main criteria:

- **Topic Relevance:** The article must specifically discuss customer profitability analysis and digitalization in the B2B market.
- **Methodological Quality:** The article must use an appropriate and systematic methodological approach in analyzing customer profitability analysis and digitalization in the B2B market
- **Comprehensive Analysis:** The article must present a thorough and in-depth discussion of customer profitability analysis and digitalization in the B2B market.

Data Extraction

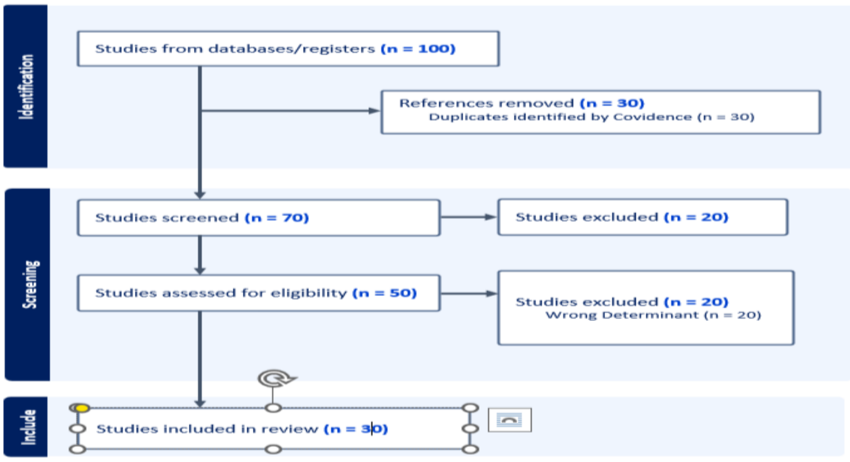

Figure 1. PRISMA- SLR

Figure 1 illustrates the PRISMA flow diagram. We used the Covidence website to conduct the systematic literature review with the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines. After searching for articles through *Publish or Perish*, we collected an initial sample of 100 studies, focusing on the systematic literature review. We excluded 30 articles identified as duplicates. We excluded articles that were not related to customer profitability, digitalization, and the B2B market. For quality assurance reasons, we only referred to studies published in Scopus-indexed international journals. This resulted in the exclusion of 70 articles and a final sample of 30 articles.

In conducting the article screening, the first step was a preliminary analysis. Preliminary analysis is a scan of the article titles and research abstracts relevant to the research to be conducted. We did not further consider articles with titles and abstracts that did not align with our research objectives. The next step was selecting articles by scanning the theories and methods used. After the article screening was complete, we categorized several articles based on the independent and dependent variables studied in Customer Profitability Analysis and Digitalization. Furthermore, the research sample used was the B2B market.

MAIN FINDINGS

This section organizes the study's findings thematically, following the structure proposed by Varsha P S et al. (2024), Votto et al. (2021), and used by Firmansyah et al. (2024). e begin by summarizing the main quantitative and qualitative aspects of the literature analyzed. Next, we review the relevant definitions and features of the field. We then examine the various modeling frameworks, as well as the areas and methods used in various customer profitability analysis cases. Furthermore, we discuss how digitalization, such as AI and Machine Learning, is utilized in prescriptive or predictive frameworks to assess customer profitability analysis. Finally, we conclude this section by highlighting the main contributions and limitations of this systematic literature review (SLR), and by defining the research agenda for this field.

Quantitative & qualitative summary of the outputs of this study

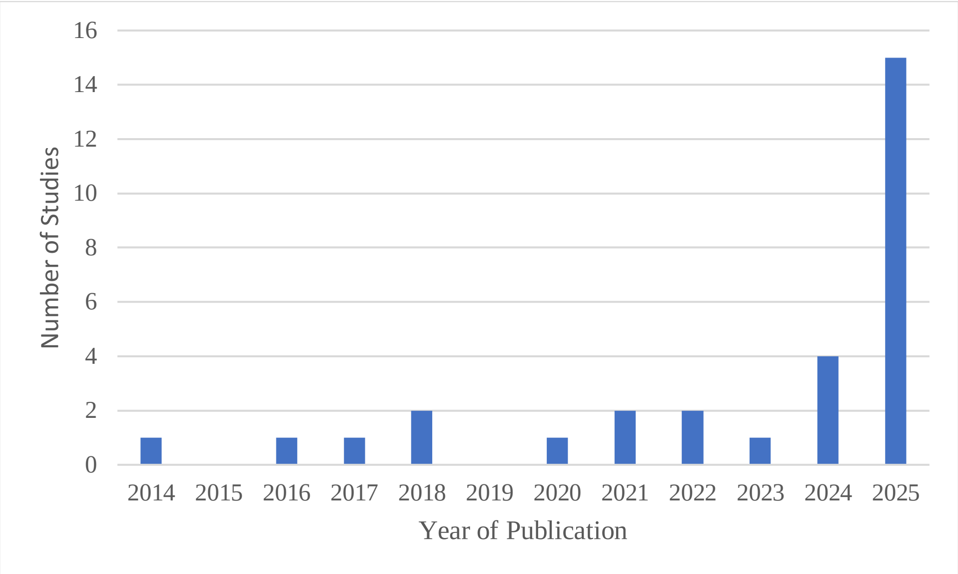

Figure 2 Number of studies by year of publication.

The SLR findings conducted in this study identified publications from 2014 to 2025, as shown in Figure 2. The first recognized study was conducted by Tamaddoni Jahromi et al. (2014), which discussed data mining techniques for modeling customer churn in the B2B context. In this year, the use of data mining to analyze customer profitability began to be discussed. After 2014, there were no publications published regarding customer profitability analysis and digitalization. However, in 2016 and 2017, one study each was identified: Lau et al. (2016) and Dawson et al. (2017). Then, 2 studies appeared in 2018, namely Zhang & Seetharaman (2018) and Jarvinen & Vaataaja (2018). Most of the research was published in journals focusing on marketing and management. Further studies emerged in 2020, leading to a surge in research studies in 2025. Specifically, 26% of studies were published in marketing journals such as *Industrial Marketing Management* and *Marketing Intelligence & Planning*, while 16% were published in retail management publications such as the *Journal of Retailing*. The remaining papers were published in alternative venues, such as *Industrial Management & Data System* and the *International Journal of Information Management*.

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Table 2 An overview of research methods and outputs of the different studies in the area.

No	**Reference**		**Research Method**			**Output**		
		Years	**LR**	**E**	**CS/VS**	**T**	**CM**	**ER**
1	Jahromi et al	2014			✓		✓	
2	Lau et al	2016			✓		✓	
3	Dawson et al	2017			✓		✓	
4	Qin Zhang and P.B. Seetharaman	2018			✓		✓	
5	Janne Jarvinen and Kim Vaataaja	2018			✓	✓		
6	Mahlamäkia et al	2020		✓				✓
7	Meyer et al	2021			✓		✓	
8	Rebeloa et al	2021			✓	✓		
9	Bonney et al	2022	✓					✓
10	Chen Lin and Douglas Bowman	2022		✓				✓
11	Lisa Lundin and Daniel Kindstr¨om	2023		✓		✓		
12	Wan Huang, Yufan Bai, Hong Luo	2024		✓				✓
13	Taheri et al	2024		✓				✓
14	Firmansyah et al	2024	✓				✓	
15	Rainer Lueg and Dima Ilieva	2024		✓		✓		
16	Oliveira et al	2025		✓	✓			✓
17	Voorhees et al	2025	✓				✓	
18	Alnofeli et al	2025		✓				✓
19	Ryu et al	2025		✓			✓	
20	Chunyu Bao, Min Li, Yiying Pei	2025		✓				✓
21	Cortezet al	2025		✓				✓
22	Shashank Vaid and Fred M. Feinberg	2025		✓				✓
23	Kyrdoda et al	2025	✓					✓
24	Almendros et al	2025		✓				✓
25	Qiang Wu et al	2025		✓				✓

26	Yang Pan et al	2025		✓				✓
27	Yavuz et al	2025		✓				✓
28	Gao et al	2025		✓				✓
29	Wijekoonet al	2025		✓				✓
30	Tzu-Lun Huang	2025		✓				✓

Table 2 displays the 30 selected papers, along with the research methodologies used and the study findings. The research methodologies used are Literature Review (LR), Experiment (E), and Comparative Study/Validation Study (CS/VS), which each produced different output categories, namely Theoretical (T), Conceptual Model (CM), and Empirical Result (ER). Studies were categorized as literature review (LR) if they discussed comprehensive concepts, advantages, disadvantages, or design principles for calculating customer value. Additionally, certain studies presented a conceptual model (CM) that refined the theoretical framework by offering a visual representation of model choices in calculating customer value with the help of digitalization such as data mining. Some studies also generated an empirical result (ER) through the use of calculations, predictions, or both to test the ability of AI-supported Customer Relationship Management to influence customer value. Furthermore, this research shows a post-sales relationship management model in the B2B market to enhance loyalty and customer value. The majority of the selected articles included a theoretical viewpoint on the field of customer value, digitalization, and customer loyalty.

Studies throughout time

The first study conducted by Tamaddoni Jahromi et al. (2014) adapted the framework proposed by Neslin et al. (2006) and Lemmens & Gupta (2013) to calculate and maximize the profitability of retention campaigns at the individual customer level in a B2B context, considering factors such as churn probability, customer value, and incentive cost. This article addressed a literature gap by proposing a data-mining approach to model customer churn in a non-contractual B2B context. Data mining, rooted in AI, is favored because churn is a rare event, and prediction accuracy is highly emphasized. Digitalization of customer retention profitability calculation was already widely researched, particularly this study used a sample of online retailer companies in Australia. This indicates that research in 2014 already considered the importance of digitalization for calculating customer retention value, especially in developed countries like Australia.

Studies in the period 2016-2020 show the development of research in the utilization of digitalization to calculate customer value across several corporate sectors, such as the research conducted by Lau et al. (2016) on an airline company. Dawson et al. (2017) developed research with empirical result output that examined the relationship of performance drivers between suppliers and customers on customer value. Meanwhile, 2 studies in 2018, namely Zhang & Seetharaman (2018) and Jarvinen & Vaataaja (2018) , used the case study technique. The use of the case study technique in this year indicates an increase in research models in the field of customer profitability analysis. While the research by Mahlamäki et al. (2020) developed the field of customer value research in the form of a digitalization tool for the sales process in the B2B market to assess customer acceptance.

The period 2021-2025 saw a surge in research with the development of more complex customer value research fields with new variables. Rebelo et al. (2021) added the variable of improved after-sales service to increase customer profitability and loyalty. Lin & Bowman (2022) linked the impact of the introduction of customer loyalty on customer profitability. Firmansyah et al. (2024) conducted a literature study regarding the gap in research related to how customer risk factors are integrated into Customer Lifetime Value (CLV) calculations in various industries. In 2025, there are 15 articles that have been selected in accordance with the field to be discussed in this study. The research methods used in these 15 articles are quite diverse, consisting of literature review, PLS-SEM, regression models, case study, bootstrapping analysis, and XGBoost and random forest algorithms. In this year, research is becoming more diverse with the fields studied and various variables such as the utilization of new tools or sales digitalization to enhance the sales process in the B2B market (Oliveira et al., 2025). Furthermore, Alnofeli et al. (2026) studied the ability of AI-assisted CRM to improve organizational

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performance. Vaid & Feinberg (2025) introduced the Digital Lead Generation Platform (DLGP), an increasingly popular way to enable users to explore products from various retailers that can improve customer satisfaction and customer value.

Digitalization, Customer Profitability Analysis, and B2B Market

The following is the result of the systematic literature review integration that provides information in the form of the research objective and research results of each article that has been selected through several selections:

Table 3 PRISMA- SLR Result

No	**Reference**	Research Theme	Research Result
1	Tamaddoni Jahromi et al. (2014)	Introducing data mining techniques to model customer churn (customers who stop) in a non-contractual B2B context and developing a retention campaign that maximizes profit.	The best performing data-mining technique (boosting) is then applied to develop a profit maximizing retention campaign. Results confirm that the model driven approach to churn prediction and developing retention strategies outperforms commonly used managerial heuristics.
2	Lau et al. (2016)	Developing a hybrid model to analyze integrated data to identify airline customers with varying profit potential for market segmentation.	This research successfully developed a multi-criteria hybrid model that integrates Activity-Based Costing and Management-based Customer Profitability Analysis with the Relationship Marketing model using the Fuzzy Analytic Hierarchy Process and TOPSIS methods to measure and rank the profitability of the top 100 corporate customer accounts of an airline.
3	Dawson et al. (2017)	Investigating performance drivers in Chinese supplier-customer relationships for two types of Chinese suppliers: International Joint Ventures (IJV) and State-Owned Enterprises (SOE).	The profitability of SOE customer relationships is related to continuous personal and hierarchical relationships, while for IJV, that profitability is related to interactive product adaptation and production planning.
4	Zhang & Seetharaman (2018)	Proposing a customer profitability model for companies whose customers have purchasing cycles determined by an intrinsic cycle and the cumulative effect of marketing demand.	The paper shows that the proposed model outperforms the benchmark model in terms of both explaining and predicting customers' purchases. The paper also demonstrates significant profit consequences to the firm if incorrect methods are used instead of the proposed method.
5	Jarvinen & Vaataaja (2018)	Investigate how companies with different customer interfaces utilize time-based activity-based costing in their customer profitability analysis.	Potential benefits for companies when modern cost accounting is connected to customer-focused operations.
6	Mahlamäki et al. (2020)	Assessing customer acceptance of a digital configurator tool in the purchasing process.	Enjoyment (comfort and pleasure in use) is the most significant predictor for customer adoption of technology, supporting the integration of intrinsic motivational aspects in B2B digital tool development.

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7	Meyer et al. (2021)	Combining customer scoring analysis and operational route planning for field sales force, to identify the most effective combination of scoring methods and tour planning models.	The Response Model (With Scores / WS) provides the best results (highest share of realized score) if its prediction accuracy is reasonable.
8	Rebelo et al. (2021)	Development and improvement of after-sales service processes to increase customer profitability and satisfaction in a Latvian manufacturing company.	After-sales service can be a competitive advantage.
9	Bonney et al. (2022)	Evaluating the implementation of digitalization in B2B business processes, particularly in marketing and sales relationships.	Digital transformation triggers business model innovation, improves customer experience, and raises challenges related to human resources and organizational processes.
10	Lin & Bowman (2022)	Investigating the impact of introducing customer loyalty programs on sales and profitability at the product category level, and the role of category characteristics as a moderator.	The introduction of loyalty programs results in an immediate spike in sales and profit in most categories, but the effect is generally short-lived.
11	Lundin & Kindström (2023)	Exploring the digitalization of the business-to-business (B2B) customer journey, which is recognized as a key research priority, but has not received substantial academic attention.	Digitalization of touchpoints (i.e., adding digital touchpoints and transforming or facilitating touchpoints), changing roles in the digitalization journey (i.e., introducing new roles, activating customers, and emphasizing collectivity), and digitalization of the overall process (i.e., expanding, enhancing, and supporting the process).
12	W. Huang et al. (2024)	Investigating whether insiders exploit confidential customer information to profit from their stock sales, using the context of the Chinese market where customer identity disclosure is voluntary.	The profitability of insider sales is significantly greater in companies that conceal customer identity.
13	Taheri et al. (2024)	Determining the factors that influence profitability, delivery time, and customer satisfaction in Omni-channel Retailing (OCR) using simulation.	The use of OCR results in the highest profit and customer satisfaction level.
14	Firmansyah et al. (2024)	Filling a gap in research related to how customer risk factors are integrated into Customer Lifetime Value (CLV)	Integrating risk factors is important for increasing the accuracy of CLV measurement and supporting customer portfolio management strategies, especially in industries with high volatility.

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		calculations in various industries.	
15	Lueg & Ilieva (2024)	Investigating the interaction between strategic goals and calculative practices, specifically Customer Profitability Analysis (CPA).	The sophistication of customer profitability analysis increases with uneven customer volume, high and controllable customer-specific burden, inter-customer interaction, and service complexity.
16	Oliveira et al. (2025)	Exploring how the adoption of sales enablement platforms (SEP) influences each stage of the business-to-business (B2B) sales process in medium-sized companies.	The adoption of Sales Enablement Platforms (SEPs) improves efficiency, collaboration, and sales performance.
17	Voorhees et al. (2025)	Integrative literature review on post-sales relationship management models in the B2B market.	B2B companies must be proactive, leverage objective data, and balance automation with human relationships.
18	Alnofeli et al. (2026)	Testing how AI-supported CRM capabilities influence organizational performance in the banking sector.	AI-CRM capabilities positively influence Marketing Ambidexterity. This Marketing Ambidexterity then improves Sustainable Profitability and Sustainable Competitive Advantage.
19	Ryu et al. (2025)	Classifying profitable customers using hotel loyalty program data.	Hotel customers tend to focus on specific divisions: Rooms, Food & Beverage, or Banquet. Profitable clusters are divided into Rooms users, F&B users, Rooms and F&B users, and F&B and Banquet users.
20	Bao et al. (2026)	Examining the impact of customer flow spillovers on the short-term and long-term strategic decisions of duopoly retailers.	Spillover effects, both unilateral and bilateral, increase retailer profitability.
21	Mora Cortez et al. (2025)	Observing the role of various actors and the changing nature of Trade Shows. The motivations for participation/actions of organizers, exhibitors, and visitors vary.	The main changes in B2B trade shows are driven by three forces: cultural, commercial, and digital.
22	Vaid & Feinberg (2025)	Introducing the Digital Lead Generation Platform (DLGP), an increasingly popular way to enable users to explore products from various retailers.	Marketplace management needs to pay attention to optimizing the number of players in each category to maximize engagement and conversion rate.
23	Kyrdoda et al. (2025)	Reviewing the dynamics and challenges of digital transformation in B2B, with the yellow cluster as an exception	Digital transformation drives business model innovation, increased efficiency, and changes in the value creation process in B2B.

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		that focuses more on quantitative approaches.	
24	Clemente-Almendros et al. (2025)	Analyzing the direct and indirect effects of digital strategic orientation on the performance of micro, small, and medium enterprises (MSMEs) in developing countries (Peru), mediated by innovation and environmental practices.	The total effect of digitalization on competitiveness is 0.401, almost double the direct effect.
25	Q. Wu et al. (2025)	Examining the influence of the CEO's Passion for Inventing (PFI) on the performance of family firms, mediated by digitalization capacity, and moderated by Socio-Emotional Wealth (SEW).	Passion For Inventing significantly influences Digitalization Capacity.
26	Pan et al. (2025)	Introducing a new tool to analyze what customers buy and how often they shop.	Consumers with similar preferences can have different shopping frequencies, which is important for promotional targeting. The model can predict shopping behavior, segmentation, price effects, promotions, and optimal bundling recommendations for revenue enhancement.
27	Yavuz & Çalik (2025)	Investigating the long-term impact of AI and Machine Learning (ML) patent intensity on the financial performance of innovation-driven companies.	AI/ML patents significantly increase ROA and Operating Margin with a five-year lag.
28	Gao et al. (2025)	Investigating the impact of AI chatbot problem-solving capabilities on user intention to continue using the service on e-commerce platforms.	The main factors influencing user intention to continue using AI chatbots: ease of use, satisfaction, and trust, as well as the effectiveness of problem solving.
29	Wijekoon et al. (2025)	Applying the strategic entrepreneurship framework and configuration theory to investigate how the combination of strategic behavior, decision-making logic, resource allocation mechanisms, and the socio-cognitive characteristics of leaders influence customer-focused performance.	The combination of effectuation-bricolage significantly increases the fit of EO-MO, which leads to customer satisfaction and customer relationship quality.
30	T.-L. Huang (2025)	Investigating the impact of Digital Transformation (DT) on the financial performance of	Market valuation increases immediately after the adoption of Digital Transformation, reflecting investor confidence in the long-term strategic value of DT.

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		publicly listed companies in China.	

The SLR study identified the existence of digitalization for calculating customer profitability analysis as explained in each collected article. Tamaddoni Jahromi et al. (2014) utilized advanced computational capabilities to process large volumes of data and identify patterns for prediction. Researchers used data mining models such as Boosting, Decision Tree, and Logistic Regression to calculate the churn probability for each customer (Coussement & De Bock, 2013). Boosting, as an ensemble learner technique, proved to be the most accurate in identifying true churners. The results of the data mining model (churn probability) are then integrated into a formula to calculate the individual profitability of targeting customers with retention incentives. This formula is the culmination of data-based analysis by Neslin et al. (2006) and Lemmens & Gupta (2013) where profit is calculated based on:

$\pi i = pi\ [\gamma i(Vip - \delta i)] + (1 - pi)\ \ [-\varphi i \delta i]$

- pi (churn probability) is derived from the data mining model (digitalization result).
- Vip (estimated revenue in the prediction period) is calculated based on (revenue generated in the calibration period) from transactional data.
- Vic itself is the Monetary variable from the RFM model.

It can be noted that the churn modeling in Jahromi et al. (2014) research is predominantly in a B2C context, and the application of data mining techniques in B2B churn prediction is still an underdeveloped area. This shows the existing opportunity to introduce various data mining modeling techniques and approaches to the area of churn prediction in a B2B context (Wiersema, 2013). The magnitude of this opportunity becomes clearer when the nature of the B2B context, with large purchases and transactions, is taken into account (Rauyruen & Miller, 2007). According to Martínez-López & Casillas (2013), the application of AI in a B2B context spans a wide range, from pricing strategies to communication decisions and product development. Of all the roles such systems can play in solving industrial marketing problems, managing customer relationships will certainly be a significant one. It has been well established in the marketing literature that, as a more profitable marketing strategy, companies should focus on building long-term relationships with their customers by adopting appropriate retention approaches, instead of striving to acquire new customers (Rebelo et al., 2021)

Lau et al. (2016) investigated the calculation of digital-based CPA with Activity-Based Costing and Management (ABC&M). Costing information is captured in process-specific data marts, which reside under a centralized multi-function repository. These data marts store micro-level transactions and also cost/activity driver tables (Lau et al., 2016). The ABC model within the data marts is dimensioned based on the customer, product, location, and resource perspectives (Ruiz-de-Arbulo-Lopez et al., 2013). This allows for the tracing of cross-functional cost and profit information specific to each customer. To address the limitations of ABC&M as a backward-looking approach, this article used a hybrid model involving two Multi-Criteria Decision Making (MCDM) techniques based on digitalization/analytics. Fuzzy Analytic Hierarchy Process (FAHP) was used to determine the weights of RM criteria and sub-criteria that influence long-term customer profitability (Erensal et al., 2006). The form of digitalization here is by converting the linguistic assessments (subjective and vague) of an expert panel into triangular fuzzy numbers (TFN). This is a form of digitalization in decision-making, which handles uncertainty in human judgment. Then, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to combine the FAHP weights with the decision matrix (actual customer data) to rank the top 100 corporate accounts based on the prospect of long-term customer profitability (Olson, 2004).

The most sophisticated digitalization aspect in Firmansyah et al. (2024) article is the integration of customer risk factors into CLV calculations, which is highly relevant for the B2B market. In the B2B market, customers can carry significant risks (e.g., high churn probability, purchase volatility, or credit risk). Digitalization enables the use of AI models to predict and adjust revenue based on Risk-Adjusted Revenue (RAR) (Singh et al., 2013). Machine Learning models such as Logistic Regression, Support Vector Machine (SVM), Neural Networks, and Random Forest are used to predict the probability of risk occurrence, such as the likelihood of churn or default.

In the context of Customer Portfolio Theory (CPT), Machine Learning models are used to measure customer purchase volatility, similar to measuring financial asset risk (Machado & Karray, 2022). All these analyses are made possible by centralized information systems that reflect operational digitalization. With digital models, managers can proactively allocate resources (e.g., retention incentives or account manager time) to maximize CLV (Return) by focusing on high-profitability customers, as well as minimizing risk (Volatility) by identifying and managing customers with unstable purchasing patterns or high churn probability.

Digitalization drives business model innovation, increased efficiency, and changes in the value creation process in the B2B market (Kyrdoda et al., 2025). In their research, Kyrdoda et al. (2025) suggest that Artificial Intelligence (AI) technology automates routine tasks and helps simplify the customer journey and enhance value co-creation. This can reduce the cost-to-serve for customers. Technologies such as Big Data Analytics offer valuable consumer and technology market insights (M. Wu et al., 2022). Digitalization enables suppliers and buyers to gather and analyze market knowledge regarding products, competitors, and customer preferences. Accurate and rapid data allows companies to refine their strategies based on market demand, improving efficiency and decision-making. Through CRM systems, AI, and chatbots, suppliers can provide customized recommendations, quick assistance, and personalized service (Gao et al., 2025). By understanding the profiles of high-profit customers, companies can target the acquisition of more profitable customers.

The Key Non-Risk Challenges in Implementing CPA in a Digitalized B2B Environment

B2B companies often have sophisticated Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM) systems that are, however, legacy (old) systems (Bonney et al., 2022). These systems were not designed to seamlessly synchronize business logic and share data. Significant investment is needed to design new interfaces, standardize data formats, and centralize business policies (business logic) so that systems can interact consistently and share information smoothly (Rapp et al., 2017). Although transactional data is abundant, the accuracy and availability of customer data are critical barriers, especially for small and medium-sized enterprises. Effective CPA requires detailed data regarding the cost-to-serve, which is often scattered across various functional systems (Lueg & Ilieva, 2024). espite large investments in digitalization, discrepancies often arise between the expected benefits (efficiency, innovation) and the actual financial results, which raises questions about how investments translate into profitability (Alnofeli et al., 2026)

The implementation of digitalized CPA demands changes in managerial culture, capabilities, and focus. The transition to virtual (digital) operations can create business uncertainty due to a lack of clear legal and regulatory norms related to digital operations (Reier Forradellas & Garay Gallastegui, 2021). The success of CRM (which is the foundation of CPA) requires a company-wide cultural shift and cross-functional collaboration. Managers must have explicit guidance on the importance of various competing goals in decision-making. Despite the existence of human-like technologies (such as AI/chatbots), the human factor—especially competence and behavioral attributes such as knowledge, skills, and attitude—remains essential for implementing digital formats and influencing value-related processes (Gao et al., 2025). Digital transformation introduces hybrid roles (e.g., digital platforms acting as both actors and resources) that blur traditional boundaries in business models. Managing the dynamics and tensions arising from these dual roles requires a new managerial approach (Mora Cortez et al., 2025). Most research tends to focus on specific digital technologies and lacks comprehensive longitudinal studies, making it difficult to record progress and transformational impacts over time.

The Gaps Exist in The Literature

Based on the results of the collected studies discussing customer profitability analysis, digitalization, and the B2B market, the literature tends to focus separately on the domain of digital technology or accounting models, rather than on the integration of the two for B2B CPA. Most reviews center on discrete digital technologies (such as Industry 4.0, social media, or AI) and their implications for B2B marketing, sales, or servitization activities. A gap exists in how these platforms systematically collect and stream the data needed by the ABC cost structure. Other research focuses on predictive models (such as AI/ML to project CLV and risk) that require cost data to calculate profitability. However, there is a lack of empirical studies that explicitly define and practice how the output of digital platforms technically triggers these risk-based CPA calculations. Short-term profitability models like ABC&M are recognized as backward-looking (Tamaddoni Jahromi et al., 2014) Although there are hybrid models (such as FAHP-TOPSIS) that attempt to integrate cost data (ABC&M) with long-term relationship criteria, this integration is still driven by expert assessment (subjective/qualitative) and is not fully automated from digital platforms.

The B2B model is based on the Actor-Resource-Activity (A-R-A) network (Mahlamäki et al., 2020). Digital transformation changes activities from transactional to relational and value-driven, and transforms resources from passive to dynamic (Bonney et al., 2022). The gap arises because traditional ABC models view activities and resources statically, making it difficult to capture the dynamic value and relational costs generated by interactions on digital platforms. The ABC&M model requires accurate tracing of costs to activities (cost drivers). The research gap lies in how digital platforms (hybrid actors) such as chatbots or e-marketplaces used by B2B customers automatically calculate and allocate very specific and varying costs (costs to serve) to customer accounts. The majority of research on B2B digital transformation is qualitative. While qualitative approaches can understand the intricacies and complexity of transformation, the implementation of CPA and the integration of digital systems require strict quantitative methodology and data-based case studies to validate the efficiency of technology platform and accounting model integration. A significant gap is the lack of longitudinal studies that can record the development of platform and ABC/CPA integration over time, which is crucial given the continuous nature of digital transformation.

Academic and practical contributions

This systematic literature review research has compiled 30 articles with the theme of customer profitability analysis, digitalization, and the B2B market. This collection of articles has provided the view that technological sophistication such as data mining, AI, and machine learning is capable of calculating customer value in various corporate sectors. The literature shows that although Machine Learning has proven accurate (e.g., Boosting in churn prediction), its application in the context of churn and CLV prediction in the B2B market is still underdeveloped. This marks a great opportunity to test various data mining and AI techniques in B2B environments characterized by large purchases and complex transactions. Furthermore, this research highlights that traditional cost accounting models such as ABC&M are backward-looking, thereby limiting managers' ability to formulate long-term CPA strategies. It was found that hybrid models that combine quantitative methods with qualitative assessment (e.g., FAHP-TOPSIS) are a solution to integrate cost data with long-term relationship criteria assessed by experts, indicating the need for more sophisticated methodology.

There is a strong academic emphasis on incorporating risk factors (such as revenue volatility and beta risk) into CLV/CPA calculations. This encourages the development of a theoretical framework for managing customers like a portfolio of financial investments (Customer Portfolio Theory). The research on CLV and risk-adjusted revenue shows that financial portfolio approaches, mean-variance, and various machine learning techniques (Boosting, Decision Tree, Logistic Regression, SVM, Neural Network, Random Forest) are well-established for predicting churn and risk, and then incorporating those probabilities into the per-customer profitability formula. Firmansyah et al. explicitly show that almost all risk-adjusted CLV models assume the availability of cost data, but the literature is very minimal in technically explaining how those costs are derived from digital systems (ERP/CRM/SCM/platforms) for CPA purposes.

In addition, most of the literature revolves around strengthening retention strategies as a more profitable marketing strategy and the role of intelligent systems in managing customer relationships. B2B Digital Transformation: A broader review highlights that digital transformation drives business model innovation and changes in the value creation process, with AI (such as chatbots and Big Data Analytics) playing a central role in automation and enhanced value co-creation. The dominance of qualitative approaches in B2B digital transformation studies indicates the need for strict quantitative methodology and data-based case studies to empirically validate the efficiency of technology platform and accounting model integration. An explicit gap is identified in the literature regarding how digital technology platforms (hybrid actors) automatically collect and allocate specific costs (costs to serve) to B2B customer accounts.

Limitation of This Research

This study faces major limitations. First, the scope of this systematic literature review (SLR) is limited by the selection of keywords and research databases used. The article selection process limited the type of publication to only scholarly journal articles (not conference papers, books, book chapters, or other formats) to ensure validity as "certified knowledge". While this improves quality, it may exclude important insights scattered in other sources. Although careful evaluation of these search parameters was conducted to ensure a comprehensive review of the topic, some relevant studies might have been excluded. This limitation suggests that future research may expand the search criteria to include more databases and keywords, potentially uncovering other relevant research.

Second, the inclusion and exclusion criteria of the review were narrowly defined, focusing only on specific types of articles. Only English-language, Scopus-indexed journal articles published between 2014 and 2025 were included, thus excluding relevant studies in other languages, periods before 2014, conference papers, books, or industry reports. Consequently, general articles discussing the area of interest but not specifically concentrating on the field were excluded, which may lead to the loss of important insights.

CONCLUSION

This SLR indicates a clear shift in B2B CPA from historical, transaction-based analysis toward predictive and risk-adjusted analysis driven by digitalization. Digitalization drives predictive and risk models, including the application of ai and machine learning for prediction. Digitalization provides large volumes of data (Big Data) that enable the use of Machine Learning (ML) and Data Mining (such as Boosting and Random Forest) to calculate churn probability and customer-specific risk (e.g., purchase volatility and beta risk). I/ML Models integrate these risk factors into Customer Lifetime Value (CLV) calculations to generate Risk-Adjusted Revenue (RAR), enabling B2B managers to allocate resources (e.g., retention incentives or account manager time) to maximize Return (CLV) while minimizing Risk (volatility).

Traditional cost accounting models, such as Activity-Based Costing and Management (ABC&M), are backward-looking and only effective for measuring short-term profitability. To address this limitation, hybrid models (e.g., FAHP-TOPSIS) are used to combine ABC&M results with qualitative assessments (through fuzzy numbers from an expert panel) regarding long-term relationship factors, indicating that B2B profitability is not yet fully automated but requires human judgment.

The successful implementation of digitalized CPA is hampered by significant non-risk challenges, including the integration gap of legacy systems. Old ERP, CRM, and SCM systems in B2B often fail to synchronize cost-to-serve data, hindering accurate cost tracing for CPA. There is a fundamental academic gap regarding how digital platforms (hybrid actors such as chatbots or e-marketplaces) systematically and automatically calculate and allocate service costs generated by digital interactions into the ABC cost structure. Overall, this research concludes that although digitalization offers powerful predictive tools (AI/ML) for managing B2B profitability and risk, companies still struggle with the technical integration of cost data and managerial adoption challenges to achieve fully automated and holistic CPA.

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