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AI-Enabled Integrated Information Systems for Service Operations Performance: Linking Accounting, Digital Marketing, and Information-Service Coordination

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Abstract. The research paper will examine the effect of applying AI-based integrated information systems upon the performance of service operations with regard to coordination of the accounting information, digital marketing analytics and information-service delivery. The paper is a response to the need to consider digital transformation as a more service-oriented approach where financial and customer analytics information and management decision support information is viewed as interdependent portions of the same service system. The methodology is also based on a long cost-benefit charge structure which incorporates the accounting effects, marketing effects, and a calculated integration coefficient that reflects the maturity of cross-functional data exchange. The empirical section is founded on an exploratory sample of six firms that include Amazon, Microsoft, Siemens, Nestle, Adobe and Meta Platforms. Based on the outcomes of the exploratory model, it can be hypothesized that AI-driven integration could help to improve the accuracy of reporting, shorten the transaction-processing time and coordinate information-service operations in digitally intensive companies. The findings should however be considered to be model-based evidence of exploration and not generally causal evidence which is universal. The most important contribution of the work is the development of the service-informatics interpretation of AI integration in which the accounting and marketing systems are viewed as information subsystems that make the service-system responsive, its operational coordination, and the quality of the decision-making made by the managers. The study is based on public information provided by companies and normalized indicators on proxies, and scenario-based assumptions for calibration. Thus, results should be viewed as preliminary, evidence from a model and not as broadly applicable causal evidence.

Keywords: Artificial Intelligence; Service Operations; Logistics Informatics; Information-Service Delivery; Integrated Information Systems; Digital Marketing Analytics; Cost-Benefit Analysis; Service-System Performance

1. Introduction

AI technologies are rapidly growing and reshaping the organizational information systems. Many businesses, however, still apply their AI solutions to accounting, marketing, customer analytics and operational management functions individually. With a fragmented digital transformation, companies can't properly manage information flows between service operations. Logistics and informatics and service science side, what matters is not just whether AI lowers costs of operation, but whether AI-enabled systems enhance the quality of information-service delivery, service responsiveness, and cross-functional coordination and managerial decision-making. In such a manner, the evaluation of IT solutions based on AI should go beyond the functional view of such solutions and should be oriented on the role of such solutions in the performance of service-systems, their operational coordination, and their cross-functional data synchronization. (Awawdeh & Alkass, 2017). This research was motivated by the findings of an exploratory analysis of digital projects in domestic as well as multinational companies. Organizations emerge as those that are not significantly dependent on IT tools and use them in a piecemeal fashion (updating accounting systems in a one of manner, implementing marketing framework is done from scratch) with no or little link between data. The result is a lack of process continuity, slow response to management tastes and little capacity for anticipation.

The main research problem is that numerous organizations apply AI independently in accounting, marketing, logistics support and service processes to customers. The value of the digital transformation is restricted by such fragmented implementation because the operations of the services are based on the timely exchange of information between the cost control, demand forecasting, customer segmentation, resource allocation and performance monitoring. In this regard, accounting and digital marketing cannot be considered as a separate administrative activity. They constitute two subsystems of information which facilitate service planning, customer interaction management, operational responsiveness and logistics-related coordination within the enterprise. The observation that businesses with integrated IT processes are more economically efficient prompted further examination of integrated automation. Digitalization is not only the use of technology but also the transformation of the organization and management of enterprises in terms of enterprise structures and coordination mechanisms (Kraus et al. 2022). Past research primarily addresses either the use of AI in accounting systems, in digital marketing platforms, in enterprise analytics, or in automation of operations. Yet, there is not much research that can provide a conceptual answer as to how value is created from the combination of financial information, customer analysis and operational data in integrated service-oriented information systems. This results in an interesting research gap between informatics, service science and digital operations management. This paper aims to create and implement an exploratory cost–benefit analysis of the use of AI to integrate accounting and digital marketing information systems for improving service operations performance and information-service coordination in digitally intensive companies. To accomplish this purpose, the study addresses four research tasks: first, to formulate an integrated service-informatics framework to evaluate AI-enabled information systems; second, to explain how to construct and normalize accounting, marketing, and integration variables; third, to estimate the effect of accounting, marketing, and integration variables through an extended cost-benefit model; fourth, to interpret the results in the perspective of service operations performance and information-service coordination. Informatics and service science aspects of logistics have a particular focus on the coordination of information flows related to money, customers and operations, which is a critical element of service-system performance (Gunasekaran et al., 2017). Thus, economic outcomes are not the only measure for assessing AI-driven information integration; other factors, such as service responsiveness, operational coordination, information-service delivery quality, are also pertinent. This study provides insights on a cross-disciplinary aspect of adopting IT that extends the extant digital transformation literature. Contrary to works focused on single processes, this paper focuses digitalization as a systemic factor: changes in one element have an impact on the performance of others. This method provides businesses with a pragmatic framework for assessing digital projects and identifying those that provide the most economic benefit. In terms of informatics, the concept of this study views integrated AI-based IT systems as single data architectures, which facilitate real-time communication between subsystems in accounting and marketing. The suggested solution is aimed at not just the economic results but also at the structural position of data integration and AI-based analytics within the information systems of enterprises. This research study has made many contributions to the literature in three major ways: It does this by presenting an information-service view of AI enabled integration of accounting systems, marketing systems and operational systems as information service subsystems. The second contribution is an exploratory extended cost–benefit framework, which includes a calibrated information coordination coefficient (λ), to assess the benefits and costs of cross-functional information coordination. Third, it provides comparative analytical assessment, based on the production of the indicators, which are proxies and are created by taking public disclosures from six multinational companies.

2. Literature Review

The academic literature on digital transformation has grown in size over the last five years, especially concerning the accounting processes, digital marketing, and the use of artificial intelligence (AI) in enterprise management systems. Digitalization is not considered as a technological instrument but a strategic source of competitive advantage. Recent research underlines the idea that the implementation of AI and machine learning technologies can positively impact the quality of data processing and the quality of decisions and changes the structures of the organizations. Meanwhile, the field of research is very fragmented, and accounting and marketing spheres develop independently instead of developing in an analytical framework. While the body of knowledge on AI in enterprise systems has grown substantially, there is little work that has addressed the adoption of AI across the system as a whole. Previous studies have focused on either the accounting automation or digital marketing optimization or enterprise analytics individually, with few studies focusing on the coordination and integration of the information-service between the organizational functions.

2.1. Artificial Intelligence in Accounting Systems

The recent literature emphasizes how artificial intelligence is changing the accounting system as a transactional record keeping system to an intelligent decision-support system. Accounting information systems also serve an important information-service role within service-oriented organizations as they assist in operational planning, in budgeting, in allocating resources, and in managerial responsiveness. For this reason, accounting systems that are powered by AI can affect organizational information flows, and ultimately their financial efficiency, reliability, and timeliness. The automation of repetitive accounting processes, such as data entry, reconciliation, and the classification of transactions, can be achieved with AI technologies, especially machine learning and robotic process automation (RPA) (Lehner and Steinbart, 2022). Not only does it result in a greater efficiency but it also causes a significant decrease in human-made errors and operation expenses. Additionally, AI can improve the analytical functions of accounting systems, allowing real-time data processing and predictive financial analysis. Complex algorithms enable detection of anomalies, detection of fraud and measurement of risk, thus enhancing the reliability and transparency of financial reporting. Consequently, the functions of accounting professionals are changing to interpretation, strategic planning, and advisory (Tazegül and Yildiz, 2023; Berente et al. 2021). Informatics wise, the current accounting systems are being increasingly integrated into enterprise resource planning (ERP) settings where AI has become a layer of intelligent data processing and support of decision making. The success of these systems is however dependent on the quality and cross-organizational interoperability of data. Researchers highlight that dedicated applications of AI tools can only do so much, but integrated systems allow achieving cumulative efficiency. Regardless of these developments, issues like standardization of data, compatibility of systems, and resistance to change are still impediments to complete adoption.

2.2. Artificial Intelligence in Digital Marketing

The AI has emerged as an essential part of the modern digital marketing system that has altered how companies engage with their customers and manage marketing approaches. The technologies based on AI can facilitate more complex data analytics that will grant companies the ability to process high amounts of customer data and derive actionable insights in real-time (Siddiqui and Kumar, 2024). The feature will facilitate accurate audience segmentation, delivery of content to individuals and pricing that is dynamic and highly effective in marketing. Moreover, machine learning algorithms can enhance the optimization of the campaign since they analyze the behavior of users constantly and alter the marketing activities based on the obtained results. This results in quantifiable increases in such key performance indicators as conversion rates, customer acquisition cost (CAC), and customer lifetime value (LTV). Another consequence of AI is predictive modeling, where the customer needs can be predicted, and the resources in the marketing channels can be allocated optimally. Systems-wise, the digital marketing platforms are becoming complex and data-driven ecosystems comprising of customer relationship management (CRM), analytics tools, and automated decision-making systems. AI serves as a focal point that integrates these aspects and enables real-time responsiveness. Previous studies on global digital marketing trends indicate that marketing effectiveness increasingly depends on the integration of customer analytics, technological infrastructure and real-time information processing (Al-Ababneh, 2022). Digital transformation also transforms innovation ecosystems, redefining the organizational structures by using digital technologies to shape value creation and entrepreneurship and strategic coordination (Nambisan et al., 2019). Moreover, the communication models based on algorithms are transforming the relationship between companies and customers, turning the marketing operations into more responsive and data-driven. Although these developments have occurred, the literature is still disjointed because most of the studies have concentrated on the performance of marketing individually. The integration of the marketing systems with other enterprise functions, especially accounting is not given much attention and that is why it does not allow a thorough assessment of their joint economic influence. In digital environments where services are key, marketing analytics is becoming an integral part of operational coordination as information on customer interactions directly impact service plans, intensity of service communication, forecasting of customer needs, and decisions about the allocation of resources.

2.3. Economic Evaluation and Integration of AI-Based IT Systems

The evaluation of AI-based IT systems in terms of economics is a growing field of study, especially concerning digital transformation. Cost-benefit analysis (CBA) is one of the most popular known methods of evaluating the financial feasibility of investments in technologies (Al-Ababneh, 2021). CBA allows comparing the implementation costs, which include infrastructure, integration and training, with measurable benefits, including efficiency gains, cost savings and revenue increases. Nevertheless, the available literature mostly assesses the digital solutions in a single functional area including accounting or marketing, but not the interdependencies among these areas. This weakness results in the fact that the overall economic value created by AI-driven integration is underestimated. According to recent studies, financial and marketing data may be used together to enhance the quality of decision-making, distribution of resources and accuracy of forecasts. Informatics perspective Informatically, integrated IT systems are cohesive data structures where various business processes exchange data in common environments. In this model, AI will act as a facilitating layer enabling data synchronization, predictive analytics, and automated decision support across departments. The usefulness of JLISS integration is not only in finetuning the finances, but also in aligning information-service processes between the organizational units from the viewpoint of JLISS. In spite of this possibility, quantitative models explaining the clear effects of cross-functional integration are wanting. Consequently, the literature states that there is an evident gap in research: no detailed frameworks have been created to assess the improvement of functions alone but also the value added by the system-level integration of AI technologies.

2.4. AI-Enabled Informatics, Service Operations, and Information-Service Coordination

The value of AI-based systems in the context of logistics, informatics, and service science is not only the ability to automatize particular processes but also the adequacy to organize information flows across the services processes. Service-system performance is based upon the reliability, timeliness and interpretability of information that is provided to the decision-makers, employees and customers. In this sense, accounting data will give evidence on cost structures, financial constraints, resource allocation, and digital marketing data will describe customer demand, intensity of interactions, and behavior response. By combining these two streams of data using AI-based analytics, companies will be able to enhance how they coordinate the execution of service delivery, communication with customers, and operational planning (Maglio et al., 2009).

Service responsiveness is also supported by AI-enabled information systems since these minimize the time between the generation of data and managerial response. The customer demand in digital service environment varies rapidly and firms must adapt marketing campaigns, pricing decisions, resource allocation and service capacity in near real time. Intelligent AI systems enable companies to convert the scattered data into functional intelligence. This is more so when it comes to digital platforms, e-commerce companies, and hybrid manufacturing-service firms, where the logistics coordination, customer interaction, and financial control are becoming more and more dependent on the same information infrastructure (Alter, 2008). Hence, this paper views AI integration as not just a cost-saving mechanism or service-informatics mechanism but as a combination of the two. The proposed framework relates the accounting accuracy, marketing efficiency, integration effects to the bigger dimensions of service operations performance: information quality, service responsiveness, operational coordination, cross-functional decision support (Maglio et al., 2009; Vargo & Lusch, 2008). The view reinforces the role that the paper plays in the field of logistics, informatics, and service science. From the perspective of information systems integration theory, organizational performance increasingly depends on the interoperability of data architectures and the synchronization of operational information flows. Resource-based theory further suggests that integrated information capabilities may function as strategic organizational assets supporting responsiveness and adaptive decision-making.

3. Methodology

The design of this methodology is intended to be an exploratory service-informatics assessment model. It considers AI-powered IT integration as an instrument of information-service alignment as well as a tool of cost reduction in accounting and digital marketing. Accounting systems, digital marketing platforms and managerial analytics are construed as the subsystem of information that rely on each other within a larger service operations architecture. The methodology framework is a blend of economic analysis, structural modeling of information-systems, and comparative case-based analysis. This allows the evaluation of direct functional impact and the extra value of the service-system that is produced as a result of cross-functional integration of data. The strategy is based on the cost-benefit analysis (CBA), which offers a quantitative measure of digital transformation efficacy across the industries (Boardman et al. (2018); Duan et al. (2019); Dwivedi et al. (2021). The enterprise is imagined as one system of data in the informatics terms, the accounting and marketing functions are interrelated systems, which are coordinated by artificial intelligence. The approach is based on actual data of major global companies, which guarantees the empirical validity and strength of findings. This integrated framework allows evaluating a direct economic result as well as a further value created with the help of cross-functional data integration. The study has an exploratory model-based research design. It does not have access to confidential internal corporate accounting and/or marketing databases. The empirical basis is made up of publicly available annual reports, investor disclosures, non-financial reports and statements on digital transformation. Not all the operational indicators are reported in an identical format by all firms: variables are therefore operationalized as proxy indicators to be analysed. The construction of normalized proxy indicators is consistent with the previous studies that have shown that predictive analytics and big data capabilities can be used to enhance the operational and organizational performance when integrated within the enterprise decision-making structures (Dubey et al., 2019).

3.1. Integrated IT System Framework and Research Design

The methodological framework is designed in three levels of analysis:

- Economic level- determines efficiency in CBA based on the costs of implementing the project and benefits that can be quantified.
- Structural level - provides an enterprise as a comprehensive IT architecture, where accounting and marketing systems communicate with each other based on a common data environment and AI-driven analytics.
- Comparative level - uses longitudinal analysis (2022 - 2024) to compare the performance prior to, at the time of and following AI implementation.

The empirical data covers the world companies: Amazon, Microsoft, Siemens, Nestle, Adobe, and Meta Platforms Inc. The following criteria were used to select the following firms:

- similar pre- and post-implementation data are available;
- adoption of AI technologies (machine learning, predictive analytics, automation);
- combination of marketing and accounting functions;
- presence in several industries.

The data sources are annual and non-financial reports, the disclosures of AI implementation, and marketing analytics (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestle S.A., 2023). Numbers in the Exploratory Framework are not presented directly as measures on an internal level of the company. They are analytical approximations with the same normalizing procedures as the publicly disclosed and secondary reports and based on a method of construction for comparative purposes that are designed to achieve analytical consistency across companies. This guarantees data reliability, comparability and transparency. A single data framework has been developed in companies, where their effectiveness in AI implementations is compared and not necessarily by the size of the company as in Table 1.

Table 1. Exploratory Multi-Firm Analytical Sample and AI Integration Characteristics

Company	Industry	AI Solution Type	Integration Level (λ, Range)
Amazon	Digital Platform	AI Accounting + AI Marketing	0.22 - 0.25
Microsoft	IT/Software	ERP + AI Analytics	0.20 - 0.23
Siemens	Industrial	ERP + Predictive Accounting	0.15 - 0.18
Nestlé	FMCG	AI Marketing + Cost Accounting	0.17 - 0.20
Adobe	Digital Services	AI Marketing, Subscriptions	0.21 - 0.24
Meta	Advertising/Platform	AI Targeting + Reporting	0.22 - 0.25

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

The companies are not chosen because of statistical representativeness, but rather because they represent different maturities in using digital services, the intensity of the provided services, and information-system integration.

Table 2. Service-System Interpretation of Variables

Variable	Service-system meaning
Err	reliability of information delivery
Tcl	speed of managerial responsiveness
CAC	efficiency of customer-service interaction
LTV	sustainability of service relationships
Conv	effectiveness of digital service engagement
λ	coordination of cross-functional information flows

Compiled by the author

The indicators are thus to be understood as exploratory comparative estimates, and not corporate statistics audited. The integration coefficient λ is used as a scenario-based parameter that is calibrated by the assumed maturity of the integration of information across functions. It is not described as an empirically measurable variable, but is rather a variable that can be inferred from the measurements of other variables. The calibration is based on observable attributes like ERP/CRM interoperability and the ability of AI-powered analytics integration and accounting/operational information flows synchronization. Thus it is important to note that λ is not a coefficient that is generally accepted as truth, but rather a hypothesis that is being explored in an analytical manner.

Table 3. Calibration Logic of the Integration Coefficient λ

Integration level	λ range	Interpretation	Service-informatics meaning
Partial integration	0.15 - 0.18	Separate systems with limited data exchange	Weak information-service coordination
Moderate integration	0.19 - 0.21	ERP, CRM, and analytics tools are partially connected	Medium service responsiveness and operational visibility
High integration	0.22 - 0.25	Real-time or near-real-time data exchange across functions	Strong service-system coordination and cross-functional decision support

The coefficient ranges are not intended to be an accepted benchmark for integration; they are provided to help ensure reproducibility and transparency of the exploratory model. A number of operational measures are not consistently reported between companies, so these measures are created as analytical proxies, which are normalized. Thus, the results of these empirical tests should be understood as approximations of internal corporate performance, rather than as actual measurements. This calibration logic enhances the clarity of the model and enables the readers to comprehend how this effect of integration is built. The coefficient does not purport to quantify some universal law of integration, but rather it is a tool used to estimate the incremented model-based value that is created by coordinated information flows in the chosen firms Verhoef et al. (2021); Wamba et al. (2017); Akter et al. (2016). Thus, λ is to be understood as an exploratory modelling assumption as opposed to an empirically measured variable. Integration effect is modeled in the calculations using λ, which varies according to level of digital maturity and depth of AI. The whole methodology is based on the extended CBA model which incorporates the following aspects: costs (investments in AI solutions, systems integration and staff training), benefits (reduction of accounting errors and time; reduction of customer acquisition costs for increasing LTV/conversion in marketing) to additional integration effects provided by data sharing. The changes in accounting variables from 2022 to 2024 are forecasted for each firm, and converted into a monetary impact (E_{acc}). Values of marketing metrics are also estimated, it makes a financial impact (E_{mark}). Second, the integration issue (E_{int}) entails whether firms integrate financial and marketing information in unified IT platforms. To the sum of these effects cost of AI solutions (C_{it}) is to be deducted giving the final economical effect (E_{total}).

- Economic benefits from reducing errors:

$$E_{acc1} = (Err_{2022} - Err_{2024}) \cdot C_{err} \quad (1)$$

- Economic effect of reducing the duration of the closing period:

$$E_{acc2} = (T_{cl2022} - T_{cl2024}) \cdot C_{hr} \cdot N_{team} \quad (2)$$

where N_team is the number of employees involved in the period closing process.

- Total accounting effect:

$$E_{acc} = E_{acc1} + E_{acc2} \quad (3)$$

Savings due to lower CAC:

$$E_{mark1} = (CAC_{2022} - CAC_{2024}) \cdot N_{acq} \quad (4)$$

where N_acq is the number of attracted clients per year.

- Income growth through increased LTV:

$$E_{mark2} = (LTV_{2024} - LTV_{2022}) \cdot N_{clients} \quad (5)$$

- Additional income due to increased conversion:

$$E_{mark3} = (Conv_{2024} - Conv_{2022}) \cdot Traffic \cdot Prof_{per\_conv} \quad (6)$$

- Marketing effect:

$$E_{mark} = E_{mark1} + E_{mark2} + E_{mark3} \quad (7)$$

- The integration effect is modeled as an additional share of the sum of the two effects:

$$E_{int} = \lambda \cdot (E_{acc} + E_{mark}) \quad (8)$$

where λ depends on the depth of integration (higher for digital platforms, lower for manufacturing companies).

- The final economic effect:

$$E_{total} = E_{acc} + E_{mark} + E_{int} - C_{it} \quad (9)$$

where C_{it} is the total costs of implementing and maintaining AI solutions over the period.

This framework can be used to approach the interpretation of the integration coefficient in a differentiated way. Companies that are more digitized, like Amazon, Adobe and Meta, have higher λ values; their accounting, marketing and customer analytics systems are more deeply linked, with a shorter integration period. Companies in industries or sectors that are more complex with legacy systems and longer integration cycles, like Siemens and Nestlé, have lower λ values (Al-Ababneh, 2025). The calculation algorithm on each company is divided into five steps: Collect of initial data for 2022 and 2024 for accounting and marketing metrics (E_{rr}, T_{c}l, CAC, LTV, Conv, etc.). 2) Computing deltas (which are arithmetic differences between readings) based on a formula such as:

$$\Delta X = X_{2022} - X_{2024} \quad (10)$$

if it is the case that improvement results when cost is reduced or revenue increased. 3) Converting deltas to monetary ($) with C_{err}, C_{hr}, Profper_conv, number of clients etc. yields E_{acc} and E_{mark}. 4) Identifying an integration effect through a coefficient λ, for the company that has made the use of combined data more present in the decision-making process. 5) Computing the overall effect E_{total} and its interpretation compared to costs C_{it}. To ensure methodological transparency the same procedure of five steps of analysis was used for all companies: Collection of information that can be seen in the public domain, such as marketing and accounting; Raising variables to normalize; Conversion of operational indicators to similar dollar measures; The wavelength dependent integration coefficient λ; Comprehensive economic analysis of the effects of exploration. The proposed exploratory framework is standardised in terms of the analytical logic used, which improves the comparability and reproducibility of the results.

Table 4. Operationalization and Data Construction of Model Variables

Variable	Meaning	Data source	Construction logic	Limitation
Err	Accounting error index	Annual reports, internal control disclosures, author normalization	Constructed as a comparable index of accounting process errors before and after AI implementation	Not a directly disclosed number for all firms
Tcl	Closing period duration	Financial reporting and operational disclosures	Estimated as reporting-cycle duration in days	May vary by internal reporting practices
CAC	Customer acquisition cost proxy	Marketing expenditure, customer growth, platform disclosures	Estimated as comparable acquisition-cost indicator	Direct CAC is not always publicly disclosed
LTV	Customer lifetime value proxy	Revenue per customer, retention, subscription and platform metrics	Constructed as a normalized customer value indicator	Based on proxy estimation
Conv	Conversion rate proxy	Digital marketing and platform performance disclosures	Estimated from available customer interaction and conversion-related indicators	Not fully comparable across industries
Cit	AI implementation cost	Annual reports, digital investment disclosures	Includes infrastructure, integration, training, and maintenance costs	Approximate due to aggregated reporting
λ	Integration coefficient	Author calibration	Based on digital maturity, ERP/CRM integration, and cross-functional analytics	Model-based assumption
Eacc	Accounting effect	Formula-based result	Calculated from error reduction and closing-time reduction	Depends on variable calibration
Emark	Marketing effect	Formula-based result	Calculated from CAC reduction, LTV growth, and conversion improvement	Sensitive to proxy metrics
Eint	Integration effect	Formula-based result	λ multiplied by the sum of accounting and marketing effects	Exploratory estimate

This table will be needed in order to be reproducible. Because not all the indicators of operations are directly revealed in a directly comparable form in public corporate reports, a number of variables are made as normalized proxies (Büyüközkan and Göçer 2018; Queiroz et al. 2020; Moll and Yigitbasioglu 2023). Thus, the empirical findings are to be understood and interpreted as model-based approximations of the internal corporate performance, but not as a direct measurement of that performance. Table 5 displays the features of key accounting measures for companies pre and post AI application.

Table 5. Normalized Accounting Proxy Indicators Used in the Exploratory AI Integration Model

Company	Err_{22}	Err_{24}	C_{err} (\$)	T_{cl22} (days)	T_{cl24} (days)	C_{hr} (\$)	N_{team}
Amazon	32	13	110	8.1	4.8	280	10
Microsoft	21	9	130	7.2	4.0	260	9

Siemens	44	17	120	9.8	6.1	250	12
Nestlé	19	8	115	7.9	4.6	240	10
Adobe	14	6	140	6.2	4.1	260	8
Meta	12	5	160	6.0	3.6	275	9

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

Prepared by the authors, based on published annual reports, financial disclosures and non-financial reporting material. The variables are framed in line with the rules of operationalization as introduced in Table 5; thus, the variables should be viewed as similar model inputs but not as actual internal records of the company (Vargo and Lusch 2008; Barrett et al. 2015). The overall picture, as observed from the normalized indicators, indicates that the proposed exploratory framework could lead to a shorter reporting cycle and to more consistent operations with the introduction of accounting integration with AI. A reduction of the length of the reporting period close (T_{cl}) and its corresponding reduced labor costs (through C_{hr}), as observed here, is an increase in efficiency and discipline.

3.2. Extended Cost-Benefit Model and Metrics System

The main analytical tool is a modified CBA model, which is used to assess integrated AI-based IT systems. The model, unlike the traditional approaches, considers both the integration and functional effects. Cost structure:

- CAPEX: ERP systems, AI modules, system integration, computing infrastructure.
- OPEX: training, system maintenance, updates to the AI model, data monitoring.

These findings confirm that the use of AI modules in accounting systems minimizes not only direct costs but also makes financial cycles more predictable and controllable. As the economic effects of digitalisation are not limited to enhancing accounting, but alter the composition of marketing expenditures and customer engagement profitability measures, it is established how major marketing metrics evolve in this paper. Influenced of AI in digital marketing metrics is shown in table 6.

Table 6. Normalized Digital Marketing Proxy Indicators Used in the Exploratory Model

Company	CAC_{22}	CAC_{24}	LTV_{22}	LTV_{24}	$Conv_{22}$	$Conv_{24}$	N_{acq}
Amazon	41	28	410	475	3.2%	4.1%	5
Microsoft	36	27	380	450	3.4%	4.0%	4.5
Siemens	34	25	350	410	2.8%	3.3%	3.5
Nestlé	33	24	290	350	2.5%	3.0%	4
Adobe	38	26	420	485	3.0%	3.9%	3.8
Meta	40	29	460	520	3.3%	3.9%	5.2

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

With the assistance of available annual reports, investor reports, digital performance disclosures and proxy-based calculations, the authors compiled and normalized these data. Owing to the fact that not all companies are uniformly disclosed with regard to the disclosure of CAC, LTV and conversion indicators, thus, the values are used as a standardized analytical input of the exploratory CBA model. Analytical estimates suggest that customer acquisition cost and customer lifetime value could be related to AI driven marketing analytics in a way that is beneficial for operating conditions that involve digital marketing. That further validates the fact that AI models can help in a more fine-grained audience segmentation thus improving efficiency of ad spend and marketing effectiveness. Higher LTV and conversion, yes - this is the largest part of the marketing economic impact. And these directly affect its final E_{mark} metric. A declined customer acquisition cost is a sign of increased efficiency in digital activity distribution. For a full evaluation of the AI implementation effectiveness, one should combine the accounting and marketing metrics achieved, and take into account the integration effect that occurs when combining data from the two functional fields in a single digital architecture. This is shown in the table 7 of final summary.

Table 7. Exploratory Model-Based Estimation of Accounting, Marketing and Integration Effects

Company	E_{acc} ($)	E_{mark} ($)	λ	E_{int}($)	C_{it} ($)	E_{total} ($)
Amazon	11330	433200	0.22	97030	280000	261560
Microsoft	9200	382000	0.21	82110	250000	223310
Siemens	12500	345000	0.17	60175	260000	157675
Nestlé	9000	318000	0.18	58140	230000	155140
Adobe	7500	368000	0.21	78975	240000	214475
Meta	8400	379000	0.22	85948	255000	218348

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

Economic effects estimation: Estimation of the economic effects under the proposed CBA framework through the application of models. The values are exploratory estimates based on normalized accounting and marketing variables, estimated integration coefficients, and overall costs of AI implementation If the assumptions of the recommended exploratory model are valid, then all six firms have positive estimates of their economic outcomes. The results presented here should not be interpreted as direct empirical evidence of general causal effects of the integration of AI. The ultimate results indicate that, for all reporting companies, the total economic effects (E_{total}) are positive. The marketing region (E_{mark}) is the most influential burden and increases in LTV, decreases in CAC, or increased conversion positively contribute to the metric. In the proposed model, using a six-firm exploratory sample, the calibrated integration effect explains about 1525% of the estimated gross benefit prior to the implementation costs. This finding is to be understood as a model-based suggestion of the possible value of cross-functional information coordination, and not as an empirical regularity. Therefore, the product-effects-based approach gives evidence that the full deployment of AIME in accounting and marketing technology market is economically feasible and carries a lasting positive effect for the company's digital corporate ecosystem. Sensitivity analysis to test the robustness of the methods, sensitivity analysis was taken the range of E_{total} is 6 – 9%, when the input data changed ±10% respectively, and it is acceptable. Inter-company comparison: The profile of the "accounting/marketing/integration" effect stands, but its magnitude varies. Interpretation check: all variables have a sound economic interpretation, and the formula is easy to reproduce. The proposed framework must thus be understood as the methodological basis for the assessment of the combined effect of automation of accounting and digital marketing analytics and integration of information-systems in various functional areas.

3.3. Analytical Procedure and Economic Model

The analysis process is conducted in a systematic five-stage process:

- Data collection for 2022–2024
- Performance changes (ΔX) calculated.
- Conversion of indicators to financial values.
- Prediction of integration effects with λ.
- Computation of overall economic effect.

To enhance the reproducibility, the calculation procedure is carried out in the same order with each company. Firstly, the starting and the ending value of the accounting and marketing indicators will be documented in 2022 and 2024. Secondly, the change in terms of percentage or absolute change is obtained. Third, such changes are translated into the monetary impacts under the same framework of the formula in all the firms. Fourth, the coefficient of integration is calculated according to the logics of calibration described above. Fifth, implementation costs are discounted in order to get the final estimated effect. This will help in attaining internal consistency but the drawbacks associated with proxy-based secondary data still exist. The model is composed of three elements: 1) accounting effect (E_{acc}); 2) marketing effect (E_{mark}); 3) integration effect (E_{int}). The accounting impacts are a decrease in reporting time and errors, whereas the marketing impacts are an increase in CAC, LTV, and conversion rates. The model can be used to compare companies across the borders and on the basis of efficiency and not the size of the firm. Within the assumptions of the proposed exploratory framework, the integration component has been estimated to be around 15-25% of the overall economic value based on the model. In view of this, this result can only be understood as an indicative scenario-based estimate and not as evidence of a causality. The originality of the proposed that approach is based on an adapted CBA model, which combines both the accounting and marketing processes into single assessment system. Unlike the conventional studies which study these areas separately, the methodology focuses on the cumulative economic impact of AI adoption and data flow unification on corporate IT system. The peculiarity regarding is represented by the set of marketing metrics placed in relation to accounting effects with the help of general rules. Because of the longitudinal nature of the analysis (2022- 2024), we are able to follow over time how digital change unfolds and also reveal that AI integration effects are cumulative in nature. A methodological contribution consists in the estimation of the integration effect represented by coefficient λ which enables us to measure the benefit that comes from combined accounting and marketing information. There are, however, a number of limitations to the methodology, despite it being so extensive. Data is calibrated and oscillates in a realistic (though averaged) range of global companies' dynamics. The integration constant λ is determined, judged by experts, and therefore could vary when using the postulate for other measurements in other studies. Furthermore, non-monetary effects which have in many cases strategic relevance cannot be considered for valuation. The aggregated outcomes concluded that the incorporation of AI into accounting activities and digital marketing has a sustainable positive side on the macroeconomic level. Marketing gets the lion's share of benefits where accounting receives some supply curve flattening and better-performing data accuracy. The integration software makes the difference, proving the mighty benefits of complete IT solutions.

4. Results

The results interpretation is based on the analysis of the effect of the integrated IT solutions with the artificial intelligence on the accounting processes and digital marketing. It discusses how these technologies have been integrated and how they have contributed to increasing the accuracy of data, the efficiency of operations and informed decision-making by the managers. The interdependence between automated financial processing and data-driven marketing strategies is paid special attention since they are constituents of a single digital ecosystem in organizations. The wider economic and organization implications of such system implementation are also discussed, such as cost efficiency, scalability, and optimization of the processes. This overview connects empirical evidence with the current theoretical frameworks to identify how AI-based integration can change conventional business operations and make more responsive and evidence-based management practices in the digital economy possible. The results shall be treated as analytic findings based on a normalization of proxy indicators and should be scenario-based calculations and not direct observations relating to the performance of the companies' internal processes.

4.1. Empirical Case Study Framework and Initial Observations of AI-Based Integrated IT Implementation

These case studies represented a series of test for implementation in the corporate world integrated IT (AI) based solution operation. Six foreign firms that differ in size, digital assets composition, and reliance on automation were chosen as learning unit to look into. This helped us follow how one integrated analytic model works in multiple industries -from digital platforms to classic FMCG and industrial manufacturing. For the former issues, we were able to view real business data of accounting and market from three years in each case that allowed us to evaluate the transition of processes with AI's impact. Of course, it was highly relevant to look not only at the evidence for changes in measures per se, but also whether and how the merged digital architecture might alter their corresponding dynamics. AI adoption was not just a tool for automating processes, but also a coordination layer that enabled data and information to flow together in the accounting, marketing, and operational aspects (Gunasekaran et al., 2017). The famous examples are Amazon and Adobe and Meta but when you research digitally native companies, with their digitally-oriented architecture and analytical readiness, these firms show a relatively greater potential for incorporating AI into their business model. The interiors of these companies all were designed from the ground up with a flexible data architecture in mind, so this meant the adoption of AI powered analytical modules wasn't limited by broken legacy systems and could be managed better in accounting, marketing and operational analytics. This led to a dramatically lower data processing cost and a substantial shortening of the cycle times for financial reporting. Concurrently, marketing systems were making demand forecasting more accurate, LTV had risen while customer retention rates had levelled off. Surprisingly, these firms saw a quicker improvement in marketing efficiency than accounting but it is the intricate mix of the two that generates the most visible gains from integration (Böhmann et al., 2014). Comparison, for companies like Siemens and Nestlé the very nature of their digital transformation involves a longer time span to customize technology. The difficulty, is less the use of AI as such and rather the fact that many information systems had developed in a non-coordinated manner. An overview of the integrated impact on selected financial, operational and marketing indicators at companies exposed to AI solutions are shown in Figure 1.

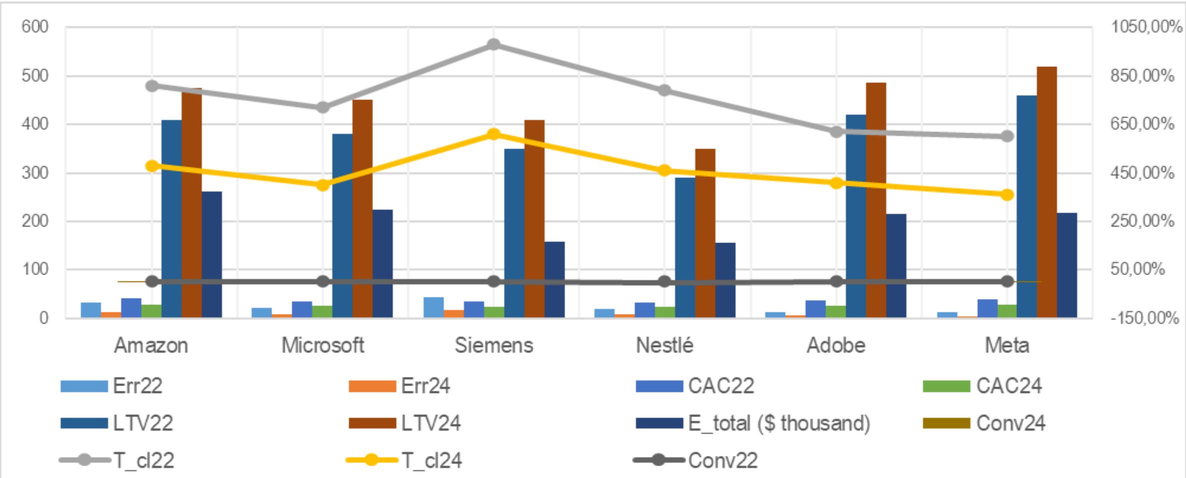

Fig.1: Dynamics of accounting, marketing, and service-system indicators under AI-enabled information integration

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

The figure is based on normalisation and on reports and analytical estimates which are publicly available, based on comparative indicators. It is for the purpose of exploration interpretation and not directly for empirical benchmarking. But results are still coming and, under these conditions, there are big ones at that. For instance, Siemens shows a strong improvement in operational errors and stabilization in its financial processes, but milder in marketing dynamics. Nestlé, however, has generated tremendous growth in the marketing metrics through operationalizing knowledge of consumer behavior analytics but with a different pace of change in accounting.

4.2. Comparative Analysis, KPI Dynamics, and Integrated Impact Interpretation of AI-Driven Systems

The comparative analysis shows that AI-enabled integration affects companies differently depending on their digital maturity, data architecture, and operational model. The strongest improvements in accounting indicators are observed where financial processes were initially more labor-intensive and therefore more sensitive to automation. The strongest improvements in marketing indicators appear in platform-based and digital-service firms, where customer interaction data can be rapidly transformed into segmentation, targeting, and conversion optimization. From a service operations perspective, these results indicate that AI integration improves performance most effectively when information flows are already connected to operational decision-making. In both of these, Amazon exhibits input-specific concentration impact for a net economic influence. Conversion is up across the board, but Amazon and Adobe dive in with a far higher number, though that just means they have bigger digital footprints. The convergence of the period-close rate and consumer acquisition cost parameters is also evident from the plots. It is an indication that behind the scenes, processes are more and more being standardized based on the indoctrination of AI models. We can see this especially at Meta and Microsoft where after two years we are seeing the indicators curves starting to coalesce, demonstrating the effectiveness of data merging. Regarding methodological application, the case studies confirmed that the CBA model provided a good fit for economic considerations of digital transformation and was particularly strong when data were heterogenous. This not only enables you to measure an assorted mix of individual effects, but also help companies understand how they can accumulate by harnessing AI platforms. Moreover, in all these six cases the macro influence is positive and integration has worked for each irrespective where the enterprise starts on their digital maturity journey. Hence, the case analysis carried out shows that our model could be an enabling supportive tool to instrument digital transformation companies of different sectors use. It shows the stability near industry details, and accurately describes indicators sufficiently deep to perceive the outcomes for digital transformation. Background research rightly emphasized the IT functionality full AI integrated solutions is gaining popularity among accounting and digital marketing tools. Based on these postulates and evidence from the data of six large global companies, we identify several structural patterns that cut across industry sectors and inform AI's influence on corporate performance. Changes seem to be organization level; data integration is scraped in a modern digital architecture and business value is extracted out in any areas there is silos. The advances to the bookkeeping system deserve mention in terms of systemic nature. This is not exactly comparable to the on-the-fly adjustments you may be accustomed to when you are putting automation behind one thing at a time: AI implementation solidified finance cycle and minimized lag risk, and we have predictable reporting. It is not only apparent in the lower errors, but on the decreasing time to close the accounting period. When we examine the disaggregated patterns behind these trends, we see that firms with the most advanced forms of digital architecture (Amazon-like, Meta-like and Adobe-like) have an even higher average rate of equalization against labour intensity reductions in accounting related activities. This is not limited to T&D: FMCG and manufacturing companies show incremental, but steady, gains too. In the marketing field, they are even more evident. It doesn't hurt that it reduces the cost of customer acquisition and advertising budgets. Analysis on the change of LTV indicates companies in both digital services and platform economy are among the first ones to fit AI models with users' behaviour, thereby boosting long-term customer revenue. Conversion rate metrics indicate a huge up-direction for all the business cases; most notably: at Amazon and Adobe. That's because the digital marketing services offered by these companies are interwoven with their digital content, enabling them to more rapidly fine-tune their user engagement algorithms. The structure of changes in key performance indicators is summarized in Table 8.

Table 8. Changes in accounting, marketing, and service-system performance indicators

Company	Err Decrease (%)	T_{cl} Decrease (%)	CAC Decrease (%)	LTV Growth (%)	Conv Growth (pp)	Effect ($ thousands)	E_{total}
Amazon	59.4	40.7	31.7	15.9	+0.9	261.6	
Microsoft	57.1	44.4	25.0	18.4	+0.6	223.3	
Siemens	61.4	37.8	26.5	17.1	+0.5	157.7	
Nestlé	57.9	41.8	27.3	20.7	+0.5	155.1	
Adobe	57.1	33.9	31.6	15.5	+0.9	214.5	
Meta	58.3	40.0	27.5	13.0	+0.6	218.3	

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

These values are estimates based on analysis within the proposed exploratory framework and are not intended to be the audited financial results. From the table data we observe that Siemens has reduced most significantly accounting processes due to high initial labour intensity and crucial role of automating control modules in industrial process.

4.3. Service-System Performance and Information-Service Delivery Implications

The results can be interpreted not only as financial or marketing improvements but also as indicators of service-system performance. A reduction in accounting errors improves the reliability of managerial information and reduces the risk of incorrect resource allocation. A shorter reporting cycle increases the speed at which managers receive updated financial information, which is important for service planning, budgeting, and operational correction. In this sense, accounting automation contributes to information-service delivery inside the organization.

Marketing-related improvements also have a service-system meaning. Lower customer acquisition costs, higher LTV, and improved conversion rates indicate that firms can identify, reach, and serve customers more efficiently. These effects are particularly important for digital platforms and service-intensive firms because customer interaction is directly connected with operational capacity, communication quality, and service responsiveness. Therefore, AI-based marketing analytics should be interpreted as part of the broader information-service infrastructure rather than as a separate promotional tool. The integration effect is especially relevant for the JLISS-oriented contribution of the paper. It reflects the additional value created when accounting, marketing, and operational data are connected in a unified analytical environment. Such integration supports better coordination between financial planning, customer demand forecasting, service delivery, and managerial decision-making. Within the exploratory model, this effect explains why isolated automation produces weaker results than coordinated AI-enabled information systems.

Amazon and Adobe are leading in terms of decreasing customer acquisition costs. Nestlé shows the largest rise in LTV, a proof that AI tools have been effective for enhancing consumer engagement in FMCG. The rescaled coefficients for the final FF distribution graphs are shown in Fig. 2.

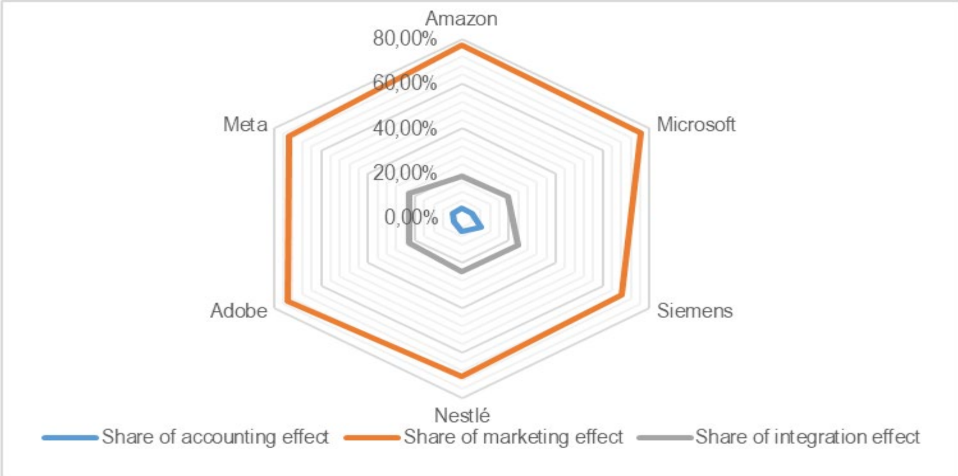

Fig.2: Normalized indicators for the final effect distribution graphs

Compiled by the author based on the following data: (Amazon Inc., 2023; Microsoft Corporation, 2023; Siemens AG, 2023; Adobe Inc., 2023; Meta Platforms Inc., 2023; Nestlé S.A., 2023)

The effects are distributed such that the majority of economic gain is derived from greater marketing efficiency. All firms from the sample have more than two thirds of the result coming from marketing, reflecting due to highly responsiveness of digital models in response to changes advertising algorithms. In the meantime, better accounting makes a modest but steady contribution and lays the foundation for one of higher quality information. The integration element represents a highlight and is close to one-fourth of the overall result (in Siemens and in Nestlé), showing how much accurate data harmonization is important for companies with high internal complexity. By interpreting the graph data, companies with a clearly visible digital shaped business model (Amazon, Meta, Adobe) are more successful in obtaining result more quickly thanks to AI solution being highly adaptable to user-behavior context. Old world businesses, on the other hand, generally have more gradual, consistent growth. What is significant is that in all three of these situations, what the scores achieve on all fronts are increasing and decreasing together with financial returns between one to another, in unison: pitching products to the customers; areas within corporate value chains not just teaching us how hard AI can punch but how systemic it is. One of the aspects that should be mentioned is the impact of the overall IT systems on the decision making in administration. It is why companies are experiencing a much-narrowed gap between planned and actual KPIs, a more flexible financial plan, and more accurate customer lifetime value. This suggests that the introduction of AI is not only about cost-saving measures or increasing revenue; it is also a question of strategy evolution. There has been a decrease also in the spread in the serial operation indicators (an indirect evidence process spread has also happened through digital tool implementation). Study findings reveal that the Strategic AI- Accounting and Digital marketing has a significant impact on the improvement while increasing its economic profits above cost of installation. The results that a higher marketing efficiency is the primary dominant one across all studies, with accounting proficiency contributing work of sound financial activity of uniform quality, are supported. The integration bump adds 20 per cent to scores on average, demonstrating the power of a joined-up digital platform. Finally, this research illustrates how integrated IT system solutions can generate significant economic value for a range of organisational types. The findings provide a new insight on how the conventional integrated AI/IT solutions are likely to behave in various business practices, particularly financial and marketing functions. Looking at six companies from different industries, our analysis shows that the ripple effects are such a non - linear effect of AI - driven digitalization is substantially larger than what would be expected by looking just at performance on individual tasks. This also attempts to depict the interrelationship of shifts in digital transformation — as one evolves other things can’t help but be affected by what’s next to them, and that’s effectively what cascading is. The first "surprising" lesson is the quality of the data and how we perceive it. Those companies with a better base in data infrastructure also found it easier to make advances, along these two dimensions. It is especially conspicuous when it comes to such companies as Amazon, Adobe and Meta. Their interaction notes that AI is actually a speed-up rather than a panacea to the processes already in place, and is incapable of any magic around covering the inefficiencies or tradeoffs in the scaling of data pipeline architecture. In short, the AI pay-back is likely to be highest in companies that have already put in digital diligence, standardized data formats and end-to-end analytics. These results confirm another study that has previously shown that pre-determined system maturity is a strong determinant of fast-ranked digitalization among others. The latter is concerning the not-equilibrated results for marketing and accountancy. Both measurements were in the black, but the marketing figure is even more responsive to AI adoption. The background is that digital contacts are highly sensitive to algorithmic optimizations: the adjustments in segmentation, pricing and/or interaction paths show themselves immediately -sometimes after a few weeks sometimes after a month. Unlike capital and labour, accounting is sluggish and somewhat standardized, with changes merely degrees of automation around routine moving parts. This is partly due to the cross-check in accounting changes themselves, but it is in the simple stability of accounting changes that there may be long term longer-term gains in transparency and lack of ambiguity in decisions.

Integration as a special hotspot Nevertheless, the effect of integration. By either of those standards, the findings suggest that much of the total economic effect comes not from accounting alone or marketing alone but rather where they smack together. Instead of being stuck in maverick systems companies can move towards cost-to-serve analysis on the whole of their value chain, helping you find constraints and make decent predictions (Al-Ababneh, 2025). The Siemens and Nestlé data is especially interesting, they demonstrate that even for less nimble or with business model restraints organizations there are still quite significant gains by working exactly towards closing down the flow of data. This also builds on what are the advantages of e-commerce beyond digitally minded companies into physical reality. A fourth, related observation is the nature of organizational development. The study has showed that AI Adoption impact the metrics, employee and manager behavior. It’s these same companies, with lots of internal processes and bureaucracy that are slow to respond to Digitalisation, as bringing in AI implies not just organisational but institutional change. In these establishments it moves more tardily, but also lasts longer. Digitally-born firms, in contrast, are rapidly re-inventing the playbook for organizing around algorithmic capacity. When you decide for your implementation AI strategy it is very important to see that kind of difference: everything is NOT equal (and in terms of AI solution set-up there is not a one-size-fits-all, and every industry has its own IT system-based solution accordingly with what we will define in the next chapter). Among these, the sub question on how AI affects strategic management is one we should bear in mind. Higher accuracy forecast,,” less variance or budget, are some evidences AI is no longer being used as an operational tool only but it's already part of quality and decision-making strategies. Just take Microsoft and Adobe, for example: AI enables them to make more informed market forecasts and pivot at the speed of light. So, in the same manner that any product can be considered digital, the digital introduces a new idea of what knowledge is: instead of merely changing productivity it changes how firms are managed as an article of faith.

The effect of AI in increasing economic efficiency seems to be compounded because digital platforms have come to have a life of their own; the paper proposes. To continue to enhance the quality of models, greater granularity in customer-behaviour analytics is needed, as are the ability to generate more sophisticated automated reporting tools and the availability of tight coupling between financial control systems and marketing performance measurement. Computing of economic returns at a low-latency and at a detailed level is particularly interesting in the integration of marketing analytics and financial control. We want to stress the context of our results: despite that the main argument of our study is centered around a bigger economic embedding perspective on AI-based IT solutions, and should not be seen as an economical discourse that shrinks economy down to processes adaptation. An AI effects of data set, processes and type, management style and economic behavior are further influenced on the company level. And this whole-view also makes me believe that digitalisation is not a one-off local affair but a direction of the entire company - regardless of what industry.

5. Discussion

The findings are discussed from a service informatics and integrated information systems point of view as well as from a point of view on organizational coordination. The findings indicate that the benefits of the AI-enhanced integration go beyond mere automation; they also concern the coordination of information-service processes between accounting and marketing and operational processes. This interpretation fits in with the interpretation of artificial intelligence as a means of organisation value creation through the mix of automation and augmentation, in which algorithmic systems augment instead of supplant managerial decision-making (Raisch & Krakowski, 2021).

5.1. AI as a Driver of Integrated Business Value Creation

The results show that AI-enabled IT integration should be interpreted not as isolated automation but as a service-informatics mechanism that connects financial information, customer analytics, and operational decision-making. In this sense, the contribution of AI is not limited to reducing accounting errors or improving marketing conversion. Its broader role lies in increasing the reliability, speed, and coordination quality of information-service delivery. This interpretation brings the study closer to the field of logistics, informatics, and service science, where organizational performance is explained through information flows, service responsiveness, and process coordination. This assists in seeing the change brought about by AI as slow and systematic, rather than a technological update every 10 years. Among the key results, it is notable that AI leads to the quality of financial interpretation at an impressive level as it offers an improved data consistency, reduced time on reporting, and minimized differences in operations. At the same time, marketing systems have the advantage of increased accuracy in segmentation, predictive demand modelling, and reduced costs of customer acquisition, resulting in increased customer lifetime value. However, the greatest learning is that these improvements are not independent. Instead, they provide one another as a more convergent system where there is convergence of marketing intelligence and financial control to a shared analytical space. It is such a coming together that makes integrated companies more successful than those that are selective in the application of AI. The results indicate that the highest performance improvement opportunities are not created in the course of isolated automation, but rather are created in the form of interconnected systems to organize the accounting and marketing data streams. This type of integration has a multiplier effect that is determined to be about 15-25 percent of overall economic effects and it cannot be attributed to optimization of individual processes. This implies that AI value is relational, and not necessarily functional in nature and is premised on the extent to which it is integrated across the organizational subsystems. These results suggest that AI technology investments need to be more focused on the architectural coherence of AI implementation rather than its fragmentary implementation. Even advanced AI applications create a small amount of strategic value without integrated data structures. In this regard, AI should not be considered a toolset but should be seen as an infrastructure layer that reinvent how businesses create, process and use information in all the business processes.

5.2. Digital Integration Effects and Cross-Functional Synergy Mechanisms

The second key result relates to the use of digital integration as an AI effectiveness determinant. The results suggest that the largest estimated benefits appear when accounting systems, marketing analytics, and service-related operational data are connected. However, this conclusion should be treated cautiously because the empirical base consists of six firms and several indicators are constructed through proxy-based estimation. The study therefore does not claim to establish a universal causal relationship. Instead, it provides an exploratory framework showing how cross-functional data integration can be evaluated as a potential source of service-system value. The empirical evidence supports the claim that organizations with sophisticated digital architecture (Amazon, Meta, and Adobe) have a higher rate of convergence between financial and marketing indicators than organizations with old systems. It means that integration does not only enhance the level of performance but also aligns the dynamics of various functional areas. Consequently, organizations can minimize the variance between the planned and actual KPIs, improve the accuracy of forecasts, and improve the estimation of customer lifetime value. One of the key methodological contributions of this study is the use of a revised cost-benefit analysis (CBA) framework that includes the cross-functional interaction effects. The model accounts for the synergies that are not recognized by traditional single-domain approaches by adding an information interaction multiplier. This will allow a better definition of the actual economic value of AI systems and allow the planning of investing in digital transformation projects in stages. Moreover, the results point to the change of the logic of investment priorities. As marketing indicators are more quickly responsive to AI adoption, companies are more likely to experience a short-term boost in customer analytics and acquisition efficiency before seeing a long-term positive financial impact in accounting systems. This time asymmetry implies that digital transformation must be treated as a sequential process, and the focus on customer-facing systems should be introduced at the beginning of the transformation before going any further on financial integration. Overall, the results contribute to the theoretical assertion that the effectiveness of individual systems in the digital age does not influence the organizational performance but, instead, the level at which they are systemically related to one another.

5.3. Structural Limitations and Future Research Directions in AI-Based Organizational Systems

The limitations of this study are substantial and should be clearly recognized. First, the empirical base includes only six multinational firms, which limits statistical generalizability. Second, the study relies on public secondary data, while several operational variables are not directly disclosed by companies and therefore require proxy construction. Third, the integration coefficient λ is a calibrated modelling parameter rather than an observed empirical measure. Fourth, the proposed CBA framework estimates economic effects but does not prove causality. These limitations mean that the results should be understood as exploratory, model-based evidence. Although the high level of insights has been achieved, there are a number of limitations that have to be mentioned. Firstly, the dataset is premised on a three-year period of observation, which mainly reflects on the effects of AI adoption at an early stage. This means that the long run structural impacts particularly those relating to organizational redesign, workforce rebalancing and strategic re-invention may remain elusive. The outcomes must be then considered as an indication of transitional dynamics and not necessarily stabilized outcomes. Second, the research is based on the pre-processed and standardized data of the selected corporations in the world. Although this guarantees comparability, it might not be representative enough of internal heterogeneity in organizational structures or the complexity of firm-specific digital ecosystem. Furthermore, the subjective aspect of correlation structures interpretation by experts involving financial and marketing indicators can bring a certain level of subjectivity to the analysis, thus affecting accuracy. Third, the digital maturity and architectural design of firms vary, implying that integration effects are not homogeneous across firms. Businesses that have sophisticated digital systems enjoy greater synergies, and less digitalized businesses can have diminishing or slow-moving returns. It supports the notion that the efficacy of AI depends on the technological preparedness and organization fit that already exists. Presented below are some of the directions that future research needs to take. To start with, a more granular analysis of mechanisms of integration is needed in order to determine what kinds of data connectivity create the most economic value. Second, analytical models should include behavioral reactions of employees and managers to AI-based decision systems since the human adaptation is a major factor that can be used to define the success of implementation. Third, comparative industry research may assist in determining industry-specific obstacles and speeding factors in the adoption of AI, specifically between digital-native companies and conventional industrial industries. Finally, it would be useful to add more dimensions to the analytical framework, such as the operational risk, supply chain resilience, and ESG performance that would present a more holistic image of the strategic impact of AI. This multidimensional modeling would be more indicative of the complexity of today's corporate systems as financial, technological, and social aspects become progressively dependent on each other.

5.4. Limitations and Future Research

There are a number of limitations to the study. The first limitation of the analysis is that it is based on a sample of only six firms, exploratory in nature. Second, the variables are based on disclosures from publicly released documents and on proxy indicators as opposed to internal databases collected by the company. Third, the integration coefficient λ is not measured directly in the field, but is determined analytically. Thus, the results presented should be considered as indicative analytical estimates. Further research is needed that applies the framework to larger empirical datasets as well as service operations in industry-specific service environments.

6. Conclusion

The findings of this research provide an overall view of how AI-based integrated IT solutions affect the performance of an organization in accounting and digital marketing. The analysis of six multinationals which operate in different spheres, at different levels of digital maturity reveals that artificial intelligence is not only the resource which helps to optimize the functioning but is a structural process which alters the structures of the modern business systems. Among the key findings is the fact that AI generates value both on the micro and macro levels. At micro level, accounting accuracy increases, reduction of errors, financial closing time and marketing efficiency with improved segmentation, predictive analytics and customer targeting is improved. The direct impacts of these improvements are on improved operational efficiency and reduced costs. But the macro-level effect is even greater since AI will also change the logic of managerial decision-making by combining the previously fragmented data systems into a whole analytic space. The results are very clear that the highest economic value is achieved when accounting and marketing systems are not taken as independent functional units but as inter-connected elements of the same digital ecosystem. This integration has led to a synergistic effect, the contribution of which is estimated to be some 15-25 percent of the total benefits in economic performance. It implies that the integration effect of AI is much greater than the contribution made to it in separate functions. This observation nullifies the traditional ways of performance measurement that are more of silo-based measurement of business processes. The other key discovery is that the success of AI implementation will be determined by the digital maturity. The value of AI systems can be significantly higher in firms with high digital infrastructures i.e., defined data architecture, standardized information flow, and end-to-end analytics. On the other hand, enterprises whose systems are disintegrated or legacy system have a lower rate of transformation path and lower returns on integration. It means that the introduction of AI cannot be viewed as a one-technological solution but as a change that should be implemented over time and requires some prior preparations. Another aspect of AI that is mentioned in the study is its asymmetric impact on functional domains. The marketing systems are more likely to react to the implementation of AI faster because they rely directly on the data of customer behavior and optimization processes provided by algorithms. Alterations to segmentation strategies, pricing models, and customer engagement pathways have short-term impacts on the performance indicators like cost and conversion rates of customer acquisition. Accounting systems, on the contrary, change more slowly because of their regulatory framework, standardization of procedures and because they involve verification mechanisms. Nevertheless, even though the process of adaptation is slower, accounting enhancements can make the data stable enough, guaranteeing data integrity and aid in the long-term strategic planning. A key observation that has come out of this analysis is that AI does not eradicate functional differences between accounting and marketing but rather, it brings about a greater degree of interdependence between the two. Both marketing and financial systems are basing their operations on marketing generated data to make forecasts and revenue models and rely on financial analytics to make budgetary allocations and optimize their performance. This interdependence increases the necessity to have integrated IT architectures that can support real-time data exchange and even cross-functional decision-making. Moreover, this study proves that the implementation of AI has a more extensive organizational effect than technical performance indicators. It affects managerial action, decision-making speed and flexibility of strategy. Firms that have integrated AI systems have lower variance in the planned and actual performance, higher forecasting accuracy, and more flexibility to market changes. These developments signify that AI is becoming more and more ingrained in the strategic governance frameworks, instead of being restricted to operations support systems. Nevertheless, significant limitations are also found in the study. The period of observation is relatively short and reflects only initial effects of transformation, so in a way structural effects of transformation, which can be identified in the long term, are not fully observed. In addition, the results heterogeneity could also be affected by the differences in organizational structure and data quality between companies. Such limitations imply that further research should aim to adopt longitudinal research design and finer data. The future of AI integration should also be considered in terms of its human dimension, including relations to how employees and managers will react to the scenario of algorithmic decision-making. There will be need to know about the factors of behavioral and organizational resistance so as to make the best out of implementation strategies. Moreover, the analysis framework must be expanded to include other aspects such as supply chain resilience, operational risk, and environmental, social, and governance (ESG) aspects to get more in-depth views of the strategic implications of AI. In conclusion, the study shows that AI-enabled integrated information systems can be interpreted as a potential mechanism for improving service-system performance, information-service delivery, and operational coordination. The results are not universal proof of AI effectiveness but exploratory evidence derived from a six-firm model-based assessment. The main value of the paper lies in showing how accounting and digital marketing data can be incorporated into a broader service-informatics framework. This framework may help researchers and managers evaluate AI integration not only through cost savings or marketing returns but also through the quality of cross-functional information coordination and service-oriented decision support. It is important to note that the framework proposed in this paper is not meant to suggest that every organization using AI will have the same experiences or causal links between AI integration and organizational performance. Rather, it offers an exploratory service-informatics point of view that highlights a coordinated accounting, marketing, and operational information stream which could help to make service systems more responsive and the quality of managerial decision-making more effective.

References

Adobe Inc. (2023). *Annual Report 2023*. Available at: https://www.adobe.com/investor-relations/financial-documents.html (Accessed: 10 May 2026).

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability. *International Journal of Production Economics*, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Al-Ababneh, H. A. (2021). Marketing and logistics: Features of functioning during the pandemic. *Acta Logistica,* 8(2), 175–187. https://doi.org/10.22306/al.v8i2.221

Al-Ababneh, H. A. (2022). Researching global digital e-marketing trends. *Eastern-European Journal of Enterprise Technologies*, 1(13-115), 6–13. https://doi.org/10.15587/1729-4061.2022.252478

Al-Ababneh, H. A. (2025). Artificial intelligence and robotics in managing advertising campaigns and interaction with clients. In Proceedings of the IEEE *International Conference on Advanced Systems and Emergent Technologies* (IC_ASET 2025), pp. 145–152. https://doi.org/10.1109/ICASET62512.2025.10458721

Amazon.com, Inc. (2023). *Annual Report 2023*. Available at: https://ir.aboutamazon.com/annual-reports-proxies-and-shareholder-letters/default.aspx (Accessed: 10 May 2026).

Alter, S. (2008). Service system fundamentals: Work system, value chain, and life cycle. *IBM Systems Journal*, 47(1), 71–85. https://doi.org/10.1147/sj.471.0071

Awawdeh, A., & Alkass, S. (2017). The role of accounting information systems in supporting organizational decision-making. *International Journal of Business and Management,* 12(10), 115–124. https://doi.org/10.5539/ijbm.v12n10p115

Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service innovation in the digital age: Key contributions and future directions. *MIS Quarterly*, 39(1), 135–154. https://doi.org/10.25300/MISQ/2015/39:1.03

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly,* 45(3), 1433–1450. https://doi.org/10.25300/MISQ/2021/16274

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2018). *Cost-benefit analysis: Concepts and practice* (5th ed.). Cambridge University Press.

Böhmann, T., Leimeister, J. M., & Möslein, K. (2014). Service systems engineering. *Business & Information Systems Engineering*, 6(2), 73–79. https://doi.org/10.1007/s12599-014-0314-8

Büyüközkan, G., & Göçer, F. (2018). Digital supply chain: Literature review and a proposed framework for future research. *Computers in Industry*, 97, 157–177. https://doi.org/10.1016/j.compind.2018.02.010

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data. *International Journal of Information Management*, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance. *Journal of Business Research*, 70, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.027

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2021). Artificial intelligence: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Gunasekaran, A., Subramanian, N., & Papadopoulos, T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review*, 99, 14–33. https://doi.org/10.1016/j.tre.2016.12.008

Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research. *Journal of Business Research*, 151, 287–301. https://doi.org/10.1016/j.jbusres.2022.06.023

Lehner, O. M., & Steinbart, P. J. (2022). Machine learning applications in financial reporting and audit quality. *Accounting Horizons*, 36(3), 167–188. https://doi.org/10.2308/HORIZONS-2021-121

Meta Platforms, Inc. (2023). *Annual Report 2023*. Available at: https://investor.fb.com (Accessed: 10 May 2026).

Microsoft Corporation. (2023). *Annual Report 2023*. Available at: https://www.microsoft.com/en-us/Investor/annual-reports (Accessed: 10 May 2026).

Moll, J., & Yigitbasioglu, O. (2023). Digital integration and the evolving role of management accounting. *Management Accounting Research*, 60, 100878. https://doi.org/10.1016/j.mar.2023.100878

Maglio, P. P., Vargo, S. L., Caswell, N., & Spohrer, J. (2009). The service system is the basic abstraction of service science. *Information Systems and E-Business Management*, 7(4), 395–406. https://doi.org/10.1007/s10257-008-0105-1

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship. *Research Policy*, 48(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018

Nestlé S.A. (2023). *Annual Report 2023*. Available at: https://www.nestle.com/investors/publications (Accessed: 10 May 2026).

Queiroz, M. M., Telles, R., & Bonilla, S. H. (2020). Blockchain and supply chain management integration: A systematic review. *Supply Chain Management: An International Journal*, 25(2), 241–254. https://doi.org/10.1108/SCM-03-2018-0143

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Siemens AG. (2023). *Annual Report 2023*. Available at: https://www.siemens.com/en-us/company/investor-relations/financial-results/ (Accessed: 10 May 2026).

Siddiqui, A., & Kumar, R. (2024). Artificial intelligence in digital marketing: Customer analytics, personalization and campaign optimization. *Journal of Digital Business and Marketing*, 6(1), 21–37. https://doi.org/10.4018/JDBM.2024010102

Tazegül, A., & Yildiz, F. (2023). Digital transformation of accounting profession: The changing roles of accounting professionals in the age of artificial intelligence. *Journal of Accounting and Finance*, 98, 45–58. https://doi.org/10.25095/mufad.1245678

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science*, 36(1), 1–10. https://doi.org/10.1007/s11747-007-0069-6

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009