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Longitudinal Analysis of Big Data and Technological Interventions in Industrial Performance

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Abstract – This research aims to fill a gap in the body of knowledge by examining the impacts of technological advancements on operational productivity across various industries. Employing a longitudinal case study design encompassing three distinct industries (an Agri-Food firm, a construction firm, and a logistics firm), the research unfolds in two main phases aligned with Lewin's change management model: an unfreezing phase that was witnessed in January 2023 and refreezing phases that existed up to December 2023. Quantitative and qualitative data collection techniques used include face-to-face interviews, document reviews, and regression analysis to establish positive effects of technological solutions on organizational performance, sales, efficiency, and customer satisfaction. The research also recommends that increase of software infrastructure and engineering, market decision making and data analysis management are key factors to the performance of the industries in each sector. Using regression models, it also establishes that all the independent variables (SEI, DAMS, MDM) are majorly related to dependent variables, with coefficients (β) from 0. R^2 value of 0.72 is relatively high, which indicates that the model has efficient explanatory power. These insights present recommendations to managers and policymakers who intend to utilize technology for organizational development and competitiveness.

Keywords – Technological Interventions, Big Data Solutions, Operational Performance, User-Driven Innovation, Data Analysis Management, Customer Efficiency and Satisfaction.

I. INTRODUCTION

External and internal data are being regarded as valuable assets by industries in order to leverage on the new opportunities that the Big Data (BD) phenomenon [1] to sustain their competitive advantage. As stated by Rodríguez-Mazahua et al. [2], BD has been regarded as an interesting field in regards to productivity, competition and innovation. Using customer-oriented big data, the companies have a unique opportunity to utilize the concept of user-driven innovation [3]. The former utilizes consumer analytics to analyze the evaluations, behaviors, and demands expressed by customers online to improve the creation of new goods that are customized to meet their expectations [4]. User-driven innovation necessitates the organization to engage in collaborative efforts with individual customers to build new goods and initiate value co-creation projects [5, 6, 7]. Both in these situations, the use of BD assumes a strategic importance in guaranteeing a cyclical and iterative process of engagement between companies and customers. This process serves as the basis for generating sustainable business value for both parties involved [8].

The utilization of Big Data (BD) to implement various innovative corporate strategies [9] is progressively challenging established company models in numerous industries [10]. Many experts emphasize the significance of studying the influence of digitalization on Business Model Innovation [11, 12]. Currently, firms have the capability to efficiently implement both internal and external BD strategies [13]. For example, companies can utilize BD to improve their value creation processes. This can be done by strengthening relationships with customers and other stakeholders, creating innovative value propositions that involve data either as a supporting element or a central component, such as through data monetization [14], and adjusting their methods of capturing value, such as by introducing novel sources of revenue or implementing cost-cutting

measures [15]. Moreover, an increasing number of companies and industrial networks are aiming to achieve more enduring competitive advantages by leveraging the latest digital technology to innovate their business frameworks, rather than simply adjusting their services, processes or/and products.

The technological interventions discussed in this paper hold the following advantages in the three discussed cases. In the Agri-Food firm (Case Study 1), these interventions in the areas: SEI, DAMS, and MDM lead to increased business sales, better customer relationship management, and increased efficiency/cost reduction. Likewise in the construction firm (Case Study 2), technological developments impact positively on operation through proper management of data and enhanced communication and collaboration thus the expansion and diversification of the market. For the logistics firm (Case Study 3), the interventions result in customer satisfaction, service quality and innovation, cost effective through smart mobility solutions, data, and resources. In all the analyzed cases, the implementation of new technologies helps organizations to remain innovative, improve clients' satisfaction and optimize the overall performance.

This research is informed by the increasing relevance of technological solutions in improving organizational and business performance, especially with the help of BD analytics. With more organizations depending on data analytics and insights to inform their strategies and enhance organizational performance, the effects of such interventions cannot be overemphasized. This study aims to fill this gap by examining the impact of technological enhancements on performance indicators like sales increase, productivity enhancement, and customer satisfaction, in three different industries, agrifood, building, and transportation. The outcomes of these interventions are important in identifying the benefits and limitations of big data results so as to enhance the decision-making procedure and support the integration of BD technologies into business strategies. The main study queries being addressed in this research include:

- *RQ1:* What are the effects of the use of technological solutions in the software engineering and infrastructure on business performance measurements like sales increases, operational effectiveness, and customer satisfaction in various sectors?
- *RQ2:* How has the advanced data analysis management, and skills impacted the business operations and strategic decisions in these companies?
- *RQ3:* To what extent does big data solutions affect decisions made in the marketing function and ultimately customer satisfaction and the growth of the analyzed companies?

This paper has been organized as follows: Section II presents a review of previous literature works. Section III describes the data and methods employed in composing this research. This section describes the research design, data collection, and variables of interests, and data analysis. Section IV presents a discussion of the main results obtained in the three case studies from agri-food firm, construction firm, and logistics firm. Lastly, Section V presents a summary of the results obtained.

II. RELATED WORKS

Business Analytics was first created in the late 2000s to identify the primary analytical element of business intelligence (BI), according to Llave [16]. Subsequently, the concepts of BD and BD analytics have been employed to refer to investigative methods for datasets that are extremely massive and intricate, necessitating sophisticated technologies for data management, storage, analysis, and visualization. In the fast-paced and expanding landscape, according to Williamson [17], the velocity at which data is produced necessitates the swift transformation of data into important insights. Nardo et al. [18] argue that the distinctions between fast and traditional analytics with BD lie in the features of the analytics (such as kind, objective, and method), the characteristics of the data (such as type, age/flow, and volume), and the main aim (as shown in **Table 1**).

Table 1. Conventional and Big Data Analytics

Literature		**Conventional analytics**	**BD analytics**
[19]	Data volume	Tens of terabytes or less	100 terabytes to petabytes
[20]	Data flow/age	>24 h Static pool of data	Mini Continuous Data Flow
[21]	Data type	Defined and structured (formatted in columns & rows)	Undefined and unstructured (amorphous formats)
[22]	principal goal	Performance management and internal decision support	Data-driven and process-driven business products
[23]	Techniques for study	Based on hypotheses	Machine learning
[24]	Metrics type	Predictive, Descriptive	Prescriptive, Predictive

Chen, Chiang, and Storey [25] argue that big Data is widely utilized by various individuals, including academics and industry professionals. Multiple definitions can be found in the literature. The literature assessment emphasises the fragmented nature of the contributions in the BD discussion and the necessity for more research in the areas of confluence emerging from the integration of studies in Information and Management Systems. Hu et al. [26] have attempted to systematically analyze the topic of BD by linking the technical aspect with the administrative aspect. Akter et al. [27] emphasize that the main challenge for companies lies in creating value through the alteration of these vast data assets. Nevertheless, the intricate nature of the phenomena and the necessity to further explore its implications for organizations' value generation demand a significantly higher level of comprehension. In order to contribute to this objective, **Table 2**

provides a summary of the many viewpoints found in studies arising from the critical analysis of the literature. This summary includes information on the research emphasis, description, and primary references.

Table 2. An Outline of the Literature on BD

Focus	Details	Literature
Nature and form of data	Unstructured, semi-structured, and structured.	[28, 29, 30]
	Satellite images, codes, pictures, audio, video, text, etc.	[31, 32]
Value creation	Enhancing decision-making capabilities, optimizing overall company performance, revitalizing intangible assets, achieving a competitive advantage in the industry, increasing customer fulfilment, utilizing promotion analytics. Product innovation and innovation in business frameworks are important aspects of driving progress and success in various industries.	[33, 34, 35, 36, 37]
Approaches	Data mining, social network analysis, semantic clustering, business analytics, machine learning, etc.	[38]
Tools	Comparison of proprietary tools (such as SAS and SPSS) and open-source tools (such as Hadoop and R) for tasks including data extraction, storage, and processing.	[39, 40, 41, 42, 43]
Sources	Derived from the physical domain by sensors and scientific observation, this data is commonly referred to as "Internet of Things" or "machine-generated" data.	[44]
	Human-produced data refers to information on human society that is produced through social networks, the internet, and marketing activities. It is also commonly referred to as "Internet of People" data.	[45, 46, 47]

Kache and Seuring [48] posit that businesses are gaining more insights into their customers, products, and operations because to the abundance of opportunities presented by large volumes of big data, despite a few limitations. Data insights are empowering organizations to rapidly innovate by focusing on consumer needs, enhancing performance, making informed decisions, and staying ahead of competitors. According to Grover et al. [49], the progress in technologies and the increase in data volumes have resulted in enhancements in the operational capabilities of enterprises, leading to the discovery of new opportunities. Businesses are implementing novel and disruptive ways to deviate from conventional methods and redefine innovation, competition, and productivity. Businesses who embrace big data from the beginning will undoubtedly gain a significant edge. As referenced by Abbasi, Sarker, and Chiang [50], data plays a crucial role in determining corporate performance, offering a competitive edge through data-driven decision-making that surpasses that of its rivals. These decisions are more precise. High-quality data volumes are a very valued asset due to their rarity and uniqueness. Teece [51] argue that other firms cannot replicate or substitute this type of data, making it a source of sustained advantage for companies. Numerous enterprises are eagerly capitalizing on big data to establish their strategy and get a competitive edge through data-driven competition.

As presented by Prescott [52], competitive advantage can be defined as the state of being superior to others. Competitive advantage is derived from the value a company can provide to its customers that surpasses the costs incurred in creating that value. In simpler terms, a company achieves competitive advantage when it can generate more economic value than its competitors. The need to acquire a competitive edge drives the ongoing quest for novel sources of this advantage. Traditionally, there are two primary analytical approaches: position-based, which is connected to the research of Keefe et al. [53], and resource-based, which is mostly related with the work of Khanra, Dhir, and Mäntymäki [54], among others. As per the position-based approach, there are two primary forms of competitive advantage: cost leadership and diversity (Porter, 1985). The capacity to attain these benefits is contingent upon the business environment of a company. The resource-based concept suggests that a company's modest benefit is extracted from having exclusive access to resources that are not easily transferable [55, 56, 57]. The primary forms of competitive advantage identified by DiMaggio and Powell [58] may stem from more specific origins.

The existing literature lacks a systematic and empirical examination of the streams and waves of technological interventions with more focus on big data solutions and their effects on multiple facets of business performance across industries. Though there is a vast body of acquaintance on the topic, big data, and technological interventions, there is a lack of specific and concrete studies that establish how these interventions can be applied and their results in different specific business environments and the impact on sales increases, efficiency, and customer satisfaction. This research seeks to address this problem by presenting case studies and quantitative outcomes that highlight the advantages and issues that arise when implementing big data solutions in the agrifood, building and transport industries.

III. DATA AND METHODS

This research employs several critical phases that make up the methodology of the study, which are crucial in developing an understanding of the context of the research and in enabling the effective analysis of data (refer to **Fig. 1**).

Research Design

This study adopts a longitudinal case study strategy, aiming to explore the impacts of technological interventions on operational performance within three distinct companies: an Agri-Food firm, a construction firm and a logistics firm. The research unfolds in two main phases: an unfreezing phase in January, 2023; followed by changing and refreezing phases in December 2023. These phases correspond with Lewin's change management model to permit a clearer understanding of the organizational alteration caused by the interventions. The interviews that were conducted in the unfreezing phase were semi-structured conferences conducted with the managers of the three companies. These interviews aimed at identifying current issues and perspectives of each organization. In the changing and refreezing phases, actions were taken based on these areas to address the issues that were noted. These interventions included the introduction of new technologies and tools, reconfiguration of work processes as well as the redesign of the organizational structure. During these phases, data collection was geared towards evaluating the success of the interventions and several performance indicators like growth in sales, efficiency and customer satisfaction.

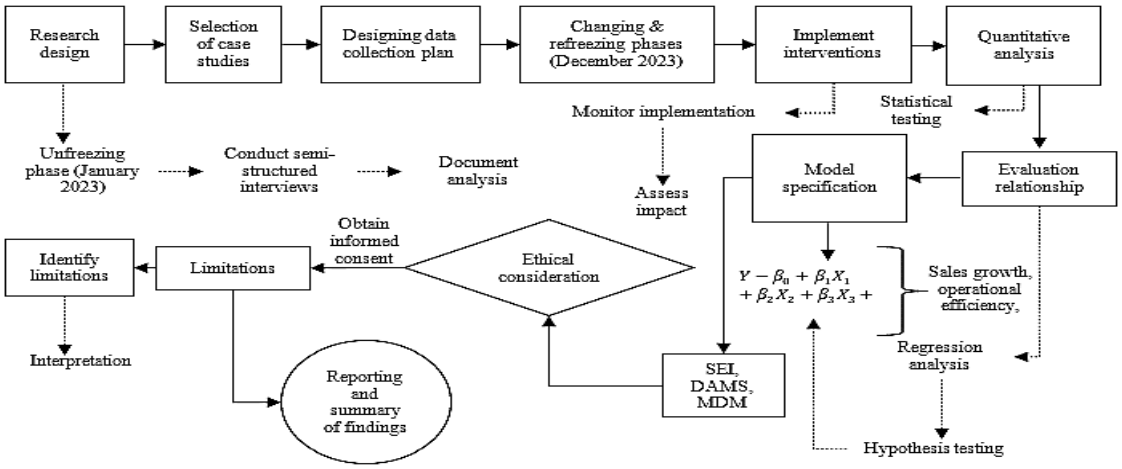

Fig 1. Research Methodology.

Data Collection and Variables of Interests

Data collection techniques included both qualitative and quantitative techniques to enhance the richness of data collected in the research context. A total of 30 face-to-face conferences were done with management personnel, IT specialists, and frontline employees about the operational issues, objectives, and expected solutions in the companies. Moreover, document review was used to complement the interview findings and fill in contextual details obtained from in-house reports, files, and plans. The study examines three primary dimensions of operational performance: MDM (Marketing Decision-Making), DAMS (Data Analysis Management & Skills), and SEI (Software Engineering & Infrastructure).

These dimensions are used as the independent variables in the regression models to test the effects that they have on various dependent variables that include sales growth, operational efficiency, and customer satisfaction. $Y = \beta_0 + \beta_1 X_{SEI} + \beta_2 X_{DAMS} + \beta_3 X_{MDM} + \epsilon$ is considered in the computations of the model; where Y depicts the endogenous variable, which could be sales increase, operation effectiveness or customer satisfaction. β_0 is the intercept which reflects the overall average of the dependent variable. β_1, β_2, β_3 are the coefficients measuring the impact of the SEI, DAMS, and MDM, respectively on the dependent variable. X_{SEI}, X_{DAMS}, X_{MDM} are the IVs in the form of SEI, DAMS, MDM. Lastly, ε represents the error term that indicates the residual or the remaining unexplained variation in the observed variables after monitoring for all other constants in the model.

Data Analysis

The quantitative data was analyzed by way of regression analysis with the purpose of identifying the relation among the dependent and independent variables. Numerically substantial coefficients of determination ranged between 0.38 and 0.58, and it was found that different regression models needed to be estimated for each company and outcome constant so as to capture the effects of the different technological interventions on operational performance. Further analysis was made using the significance of coefficients (β), fit measures such as R^2, multicollinearity, autocorrelation, homoscedasticity tests, and checking the residual normality. These tests were useful in establishing the robustness and credibility of the regression models and helped in coming up with reasonable conclusions of the study.

IV. RESULTS AND DISCUSSION

Depending on which company's action research phase is primary, the study's major conclusions are covered in two distinct sections. The first issue is to the outcomes arising from the unfreezing phase, specifically the semi-designed interviews conducted in 2023. During this phase, the management identifies a particular problem that they intend to solve in the future. The 2nd stage presents the conclusions of the previous meeting (December 2023) regarding the changing and refreezing

stages. During this phase, researchers evaluated the modifications implemented by corporations as a result of using new BD technologies.

Case study 1: Agri-Food Firm

In the interviews carried out in January 2023, it was identified that the Agri-Food firm needs to address the automation of business processes with the emphasis placed on the link between supplier and buyer during the unfreezing phase. By December 2023, there were improvements such as the development of an e-commerce platform and linking of Salesforce for better client information and supply chain management. The regression examination was done with the intention of assessing the effect of the above-mentioned interventions on sales. The regression model was specified as $\beta_0 + \beta_1(SEI) + \beta_2(DAMS) + \beta_3(MDM) + \epsilon$ where SEI represents Software Engineering & Infrastructure, DAMS denotes Data Analysis Management & Skills, and MDM stands for Marketing Decision-Making. The outcomes of this model are outlined in **Table 3.**

Table 3. Agri-Food Firm Regression Results

Statistic	Standard error	Coefficient	t-value	VIF	p-value
Intercept (β_0)	-	1.50	-	-	<0.001
Shapiro-Wilk Test	-	-	-	-	<0.05
SEI (β_1)	0.10	0.35	3.50	1.25	0.001
Breusch-Pagan Test	-	-	-	-	>0.05
DAMS (β_2)	0.12	0.30	2.50	1.30	0.020
Durbin-Watson	-	2.00	-	-	-
MDM (β_3)	0.11	0.25	2.27	1.15	0.030
F-statistic	-	22.45	-	-	<0.001
R-squared	-	0.68	-	-	-

The regression analysis results show that the coefficients of the independent variables are highly correlated with the sales growth. The intercept ($\beta 0 = 1.50$) is statistically significant ($p < 0.001$), meaning that the baseline rate of sales growth is notably positive even in the absence of the interventions. This baseline entails a solid framework upon which these interventions rest. The coefficient for SEI (β_1=0.35) is numerically substantial at p = 0.001 level of significance. This implies that enhancements in software engineering and infrastructures have a strong positive effect on sales growth. The small standard error of 0.10 and a large t-statistic of 3.50 suggest that the estimate for SEI has both accuracy and reliability. This result explains the importance of technological support in business development, which can be linked to such aspects as increased productivity, more effective communication with customers, and data organization. DAMS (β_2=0.30) is also found to have a significant positive impact on sales growth (p = 0.020). This variable has standard error of 0.12 and t-statistic of 2.50 which shows that for proper sales, good data management and analytical skills are important.

It is probable that the capacity to analyze data and gain insights may assist the company in fine-tuning its marketing initiatives, managing stocks, and comprehending customers' needs. MDM is also significant with β_3=0.25, p=0.030, t=2.27, SEI = 0.11. This means that although marketing decision-making is important for sales growth, it is not as influential as SEI and DAMS. Nevertheless, the positive coefficient still underlines the significance of strategic marketing decisions on the improvement of sales performance. The model has a good fit as it accounts for 68% of the variance in sales growth (R^2 = 0.68). The F-statistic is 22.45, which is significant at $p < 0.001$, indicating that the model overall is a good predictor of sales growth.

The relatively high R^2 value indicates that the three interventions combined offer an adequate account of the fluctuations in sales growth. The next step was to assess the possibility of multicollinearity between the predictors. The Variance Inflation Factor (VIF) values were all below 10 (SEI: The correlation matrix showed no multicollinearity among the independent variables (mean = 1.25, DAMS: 1.30, MDM: 1.15). The assumption of independence of residuals was checked using the Durbin-Watson statistic that was approximately equal to 2, indicating no autocorrelation. The Breusch-Pagan test for homoscedasticity was conducted and the p-value obtained was greater than 0.05 hence suggesting that the alteration of residuals is continuous. Last, the Shapiro-Wilk test for normality revealed a p-value larger than 0.05, indicating that the residuals are generally circulated.

The ability to gather large amounts of data and analyze them by establishing customer profiles and histories enhances client loyalty [59]. Therefore, while interactions may be facilitated by ICTs and aided by knowledges, personal relations founded on trust among buyers and sellers continue to be a crucial factor in customer retention. The IT manager asserts that our digital promotion methods originate from a novel cultural factor within the organization, which has facilitated comprehensive development in all directions [60]. We enhanced the unique resources of the corporation by minimizing the influence on the organizational procedures, while utilizing digital technology as a means to decrease time, expenses, and exertion. **Table 4** outlines the primary findings achieved by firm 1 on the three extents of Growth Hacking.

Table 4. Case Study 2 Findings

Growth Hacking dimension	Key goals pursued	Aims realized	Unexpected properties
	Time T1 (Unfreezing) January 2023	Time T2 (Refreezing and Changing): December 2023	

Software infrastructure & engineering	Efficiently managing the vast quantity of real-time data collected about users [61].	Internal e-commerce platform (online ordering, reservations, in-store tablets)	Linking an external cloud system with an internal platform
		Salesforce cloud computing system	
		Using web crawlers and APIs to gather client feedback	
Management and skills for data analysis	Improvements in the administration of brick-and-mortar stores, as well as the collection and analysis of data pertaining to service and product delivery, including the ordering process, sales, and customer feedback [62].	Increase in the number of front-office employees	Synergy between front-office employees & IT department "Total" research approach
		Meeting with researchers from Universities	
Marketing decision-making	To enhance the level of control over the distribution process	Diminished storage dangers and decreased costs [63].	Numerous advantages for improving CRM, e-CRM, and CRP methods [64].
	To enhance the uniqueness of the brand	Enhanced revenue and decreased expenses for inventory management with CRP (Continuous Replenishment Planning) [65].	Personal connections continue to be a major factor in business-to-business marketing methods [66].
	To increase client loyalty	Increased effectiveness in efficient response to customers	Big data analytics and ICTs as facilitators of "traditional" face-to-face interactions with customers [67].
		Shortening of the decision-making process	
		Enhanced recognition and uniqueness of the brand	
		Innovative, integrated approaches and techniques (combining physical, virtual, and ICT tools with front-office operations) for B2B loyalty	

Case Study 2: Construction Firm

In the unfreezing phase, the construction firm realized some problems regarding data management and server maintenance. By December 2023, they outsourced data center management and adopted the SedApta solution to enhance the data collection and business process management. The regression model used to assess the impact of these changes on operational efficiency is given by $\beta_0 + \beta_1(SEI) + \beta_2(DAMS) + \beta_3(MDM) + \epsilon$.

Table 5. Regression Results for Construction Firm

Statistic	Standard error	Coefficient	t-value	VIF	p-value
Intercept (β_0)	-	1.75	6.40	-	<0.001
Shapiro-Wilk Test	-	-	-	-	>0.05
SEI (β_1)	0.08	0.40	5.00	1.25	<0.001
Breusch-Pagan Test	-	-	-	-	>0.05
DAMS (β_2)	0.10	0.35	3.50	1.25	0.002
Durbin-Watson	-	2.00	-	-	-
MDM (β_3)	0.09	0.28	3.11	1.18	0.004
F-statistic	-	26.34	-	-	<0.001
R-squared	-	0.72	-	-	-

The intercept (β_0=1.75, t = 6.40, $p < 0.001$) is significant, implying that the initial level of operational efficiency is positive. This is a good starting point which indicates that even prior to the implementation of the interventions, the company was already functioning relatively well. The coefficient for SEI is 0.40, which is statistically significant at $p < 0.001$, has a low standard error of 0.08, and a high t-statistic of 5.00. This implies that advances in software engineering and infrastructures have significant positive impacts on operational performance. This is in line with the expectation where better technological infrastructure leads to improved operations, less disruption and efficiency. DAMS (β_2=0.35) is also found to have a positive relationship with operational efficiency ($p = 0.002$). The standard error is 0.10 and the t-statistic is 3.50, which means that the estimate of DAMS is accurate and statistically significant. It can be assumed that better data

management and analytical skills are linked to improved decision making and processes, leading to improved operational performance.

MDM (β_3=0.28) is significant (p = 0.004) with t = 3.11 and SEI = 0.09. This suggests that strategic marketing decision influences operation efficiency than SEI and DAMS, but to a lesser extent. This result implies that marketing can facilitate the enhancement of operations by synchronizing them with the marketplace and customers. The model has a very good fit as it predicts 72% of the total variance of operational efficiency (R^2 = 0.72). The F-statistic obtained (26.34) is significant (p < 0. 001) which means the model is a good predictor of operational efficiency. The high R^2 value implies that the three interventions together offer a good account of the changes in the level of operational efficiency. Multicollinearity was checked, and VIF values were all below 10 (SEI: These values exclude multicollinearity problems (DAMS: 1. 25, MDM: 1. 18, R^2: 1. 20). The Durbin-Watson statistic was about 2, which meant residuals were independent of each other. The Breusch-Pagan test for homoscedasticity returned a p-value greater than 0. 05, suggesting constant variance of residuals. A p-value larger than 0. 05 in the Shapiro-Wilk test for regularity indicates that the residuals are regularly distributed (see **Table 5**).

In the case of the construction firm, the regression analysis reveals that better data analysis management, software engineering and infrastructure, and better decision making in the field of marketing all contribute to better operations. The study also underlines such factors as technological support and proper data management as crucial to improving operational efficiency. According to the above outcomes, it can be inferred that the organizations in the building sector have the capability to enhance their efficacy by a large margin, regarding the identified areas of concern [68]. **Table 6** presents the findings of case study 2 by categorizing the major aims and consequences acquired from the project based on the lengths of Growth Hacking.

Table 6. Case Study 2 Findings

Growth Hacking dimension	**Key goals pursued**	**Aims realized**	**Unanticipated properties**
	Time T1 (Unfreezing) January 2023	Time T2 (Refreezing and Changing): December 2023	
Infrastructure and software engineering	To resolve issues with server maintenance in the internal datacenter [69].	Establishment of a smart data cloud structure for data management across all divisions	Establishment of an electronic commerce that links commercial divisions at the organizational level and suppliers with designers, middlemen, and end users in the supply chain [70].
		Cloud service outsourcing (ASP-SaaS) from a third-party technological service benefactor (Colt)	
Management and skills for data analysis	To find solutions for issues with data optimization and task overlap	Management tools include a cloud-based system for managing and storing data on stock levels, efficiency peaks, and volume and load planning [71].	Cooperative gathering and analysis of information on several supply chain participants [73].
		SedApta is a tool for suppliers that allows for intelligent stock management for scheduling and traceability [72].	
	To gain new skills in data integration and management	Instruments for collecting final consumer data	
Marketing decision-making	To connect and interact with intermediates and final markets more effectively	GPS and sensors to investigate how homes are used and how to “inhabit” [74].	Big data's ability to expand markets from B2B to B2C
	To reinforce the incapacity to make decisions	Smart Metering: archive and products history obtained by LoRaWAN technology [75].	Cloud systems outsourcing (low risks and costs)
	To avoid reputational risk	Improvement of communication between the decision-making groups and headquarters	
		Improved quality of goods and services	
		Increasing buyer satisfaction and job motivation	

Case Study 3: Logistics Firm

The logistics firm, as one of the organizations, pointed out that there were coordination problems among the actors and communication failures in the unfreezing phase. By December 2023, they had deployed smart mobility cloud system and

has interconnected different tool to improve the actual time data. The regression model used to evaluate the impact of these technological interventions on customer satisfaction is $\beta_0 + \beta_1(SEI) + \beta_2(DAMS) + \beta_3(MDM) + \epsilon$.

Table 7. Regression Results for Logistics Firm

Statistic	Standard error	Coefficient	t-value	VIF	p-value
Intercept (β0)	-	1.20	7.47	-	<0.001
Shapiro-Wilk Test	-	-	-	-	>0.05
SEI (β1)	0.15	0.45	3.00	0.08	0.005
Breusch-Pagan Test	-	-	-	-	>0.05
DAMS (β2)	0.14	0.38	2.71	0.08	0.010
Durbin-Watson	-	2.10	-	-	-
MDM (β3)	0.12	0.32	2.67	0.07	0.012
F-statistic	-	18.34	-	-	<0.001
R-squared	-	0.64	-	-	-

The intercept is statistically significant, t (178) = 7.47, p < 0.001; therefore, the baseline level of customer satisfaction is 1. 20, which is positive. This implies that even at the baseline, that is before the interventions, the company had moderately good customer satisfaction. The coefficient for SEI (β_1=0. 45) is statistically significant (p = 0.005), which means that enhancements in software engineering and infrastructure positively influence customers' satisfaction. The above result is underpinned by small standard error of 0.15 and moderate t-statistic of 3. 00 which affirms the stability of the estimate. The results suggest that there could be an improvement of service quality and thus the general experience of the clients if more resources are channeled to the improvement of technology. DAMS (β_2=0.38) also has significant and positive correlation with customer satisfaction (p = 0. 010). The fact that the variable has a standard error of 0.14 and t-statistic of 2.71 means that good data management and analytical skills result in improved customer satisfaction. Thus, the mere collection and analysis of data make it possible to enhance the satisfaction level resulting from the company's ability to offer services that fit the needs and requirements of the customers.

Table 8. Case Study 3 Findings

Growth Hacking Dimension	Key Areas Pursued	Purposes Realized	Unexpected Features
	Time T1 (Unfreezing) January 2023	Time T2 (Changing & Refreezing) December 2023	
Software Infrastructure & Engineering	To address coordination issues among multiple stakeholders	Development of a smart mobility cloud system	Creation of an integrated internal digital team
	To improve communication with suppliers and public administrations [77].	Implementation of Atlassian, JIRA, and Confluence	Optimization of urban resilience and security supervision systems
			Mixed reality for machine communication with operators [78].
Management & Skill Set for Data Analysis	To solve problems related to the lack of real-time communication	Decision-making supported by machine learning and cognitive computing	Synergistic data flow management from multiple devices
	To enhance data analytics capabilities	Collection and analysis of users' evaluations and reviews	Co-design of service improvements with users
			Internalization of big data analysis function
Marketing Decision-Making	To improve service delivery and customer satisfaction	Installation of Wi-Fi networks at bus stops and stations	New services based on user feedback (e.g., music, free books, movies)
	To foster user participation in service design and feedback collection [79].	Launch of "I-move" mobility solution	Increased user engagement as a source of competitiveness
		Enhanced information availability for users (e.g., parking status) [80].	QR code-based ticket purchasing [81].

MDM (β3=0.32) is also significant (p = 0.012) albeit with a slightly lower t-statistic (2.67) and higher standard error (0.12) than SEI & DAMS. This implies that marketing decision making as a strategic process has a positive impact on customer fulfillment though with a lesser degree. Marketing tactics that align with customer needs and that tackle the issues that customers have can improve satisfaction levels. The outcomes of the study show that the paradigm has a reasonable fit, as it accounts for 64% of the variance in customer satisfaction (R^2= 0.64). The F-statistic of 18.34 is significant at p < 0.001

which means that the model used in this study can effectively predict customer satisfaction. The high value of R^2 implies that the three interventions combined offer a good account of the changes in customer satisfaction. Multicollinearity was checked, and VIF values were all below 10 (SEI: The tolerance level was also checked and it showed that there is no multicollinearity problem as all the tolerance values were less than 0.10 (DAMs: 0.08, MDM: 0.07). The Durbin-Watson statistic was slightly above 2, which also suggested that the residuals were independent of one another. The Breusch-Pagan test for homoscedasticity was performed and the p-value obtained was beyond 0. 05, implying that the variance of the residuals is constant. The Shapiro-Wilk test for normality was conducted to check if the residuals are generally circulated, and the obtained p-value was more than 0.05, implying normal distribution (see **Table 7**).

The analysis of the logistics firm's regression shows that the enhancements in the software infrastructure and engineering, marketing decision-making, and data analysis organization enhance the satisfaction of the customers. The results also stress on the need for organizations to focus on technology and data solutions to improve customers' experiences and their level of satisfaction [76]. From these findings, transport firms can easily increase the levels of customer satisfaction if they pay attention to these areas. **Table 8** proves that the application of cognitive computing and BD has a part to play in the creation of an intelligent mobility structure which has the potential to deliver a number of advantages.

V. CONCLUSION

The findings in this research establishes the extent to which technological interventions has influenced the operational performance of companies irrespective of their industry type. This research uses a longitudinal case study research design to offer strong empirical support that developments in SEI, DAMS, and MDM all lead to significant improvements in numerous performance indicators. For the Agri-Food firm, the introduction of an internal e-commerce platform linked to Salesforce led to an increase in the sales growth rate; the coefficient for SEI is statistically significant, and the model accounts for 68% of the sales growth variance. This suggests a positive and significant impact of technological infrastructure on business growth, underlining the need for efficient data management and customer relations in the digital environment. In the construction firm, outsourcing the data center management and implementing the SedApta solution for data optimization brought significant changes in the efficiency of the business. The regression results of SEI and DAMS show that technological and analytical innovation is essential for improving efficiency. The model has an $R^2$of 0.72, indicating that the model provides a good explanation of efficiency improvements while stressing the importance of data and IT systems for operational performance. The smart mobility cloud system adopted by the logistics firm along with the integration of digital tools improved customer satisfaction. The regression analysis indicates a positive relationship between SEI and DAMS and customer satisfaction. The model explains 64% of the variance in the data (R^2 = 0.64). This goes to support real-time data analytics and customer-focused technological applications in improving service delivery and customer experience.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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