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Research Article

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The Impact of Big Data Strategic Proactiveness on Accelerating the Product Life Cycle in the E-Retail Sector

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Abstract: The purpose of this work was to explore the effects of strategic proactivity of big data for product life cycle acceleration in e-retail. A sample of workers in e-retail companies and platforms in Iraq was selected. A descriptive-analytical approach was taken and a questionnaire was the main instrument for collecting data. The study sample comprised 108 respondents with a background in digital marketing, product management, data analysis, e-sales, customer service delivery and supply chain-related job roles. Strategic proactivity of big data was measured using five dimensions: customer data analysis, demand forecasting, monitoring market trends, competitor data analysis, and real-time analytics and decision support. The dependent variable, acceleration of the product life cycle, was quantified in terms of five dimensions: increase in the rate of product idea generation, increase in product development, increase in product launch, increase in product modification and improvement, and increase in product decision making (including continuation or withdrawal of products). The results showed that the level of strategic proactivity of big data in e-retail companies was high. They further revealed that the product life cycle acceleration level was high. In addition, the study results showed that the size of strategic proactivity of big data has a significant impact on the acceleration of product life cycle. The results also revealed a high positive statistically significant correlation between strategic proactivity of big data with product life cycle acceleration. Furthermore, the total of the strategic proactivity of big data accounted for a considerable amount of variance in product life cycle acceleration. The study found that big data is not a mere technical gadget, but a strategic asset that can shorten the time taken to make decisions, enhance product management and react quickly to the changes in customers, markets and competitors of e-retail companies. The study suggested enhancements to the analytical and digital infrastructure, and skills of employees to analyse data, activation of early warning systems for monitoring product demand and competition, and integration of product development, launch, modification and withdrawal decisions with real-time analytics.

Keywords: Big Data, Strategic Proactivity, Product Life Cycle, E-Retail, Customer Data Analysis, Demand Forecasting.

INTRODUCTION

As well as the ongoing massive growth in data created by e-commerce transactions, customer actions, product reviews, competitor operations, inventory management and supply chains, the e-retail industry is witnessing rapid shifts and changes. This change has turned big data into one of the key strategic assets that can not only store and analyze information after an event but can also help predict future trends, understand customer requirements and significantly boost managerial and marketing decision making processes. (Bouaissi, 2024)

In the e-retail industry, which is dynamic, competitive, easily switchable and offers numerous choices to customers, the significance of big data is growing. Businesses in this category must diligently review what customers are doing with the product, including the number of views, shopping cart additions, ratings and comments, return rates, and so on. An organisation can find out faster the trends of its customers and can make better decisions on which products to develop, launch or modify from this data. (Morimura & Sakagawa, 2023)

The idea of strategic proactiveness of big data appears to be the capacity of the organization to not only know what is going on but also to predict future trends and be proactive before its competitors. Proactive strategy is about keeping an eye on the early indicators of the market, understanding customer behaviour, predicting future demand, tracking competitors and real-time analytics for decision making. Therefore, big data turns from analysis to becoming a strategic power that can help the organization shift from reactive to proactive. (Al-Hassan & Saqour 2022)

Strategic proactiveness of big data is directly related to the product life cycle, particularly in the e-retail sector, where product life cycles have become shorter and more dynamic compared with traditional markets. Suddenly a product can go from the launch stage into the growth stage or into the decline stage, and the price/feature/packaging changes may need to be made quickly to meet shifting demand or customer reactions. Hence, hastening the product life cycle has become a relevant issue for the companies engaged in the e-retail business as the companies can reduce time taken in product development, in launch of products, early decisions regarding withdrawing or continuing the product in the market and continuous improvement of the product. (Ozdemir et al., 2024)

A few studies about big data have been carried out in the Arab context, including its application in creating marketing strategies, managerial decision making, supply chain management and competitive advantage. Likewise, several foreign research projects have explored the potential of customer analytics and agility based on customer data to boost product and e-retail performance. It is worth mentioning that most of the previous studies have been conducted on the marketing performance and managerial decision-making, or competitive advantage, rather than the role of strategic proactiveness of big data in accelerating the product life cycle, especially in the e-retail sector in Iraq. (Ibrahim، 2025)

Hence, this study aims to explore the effects of strategic proactiveness of big data on the speeding up of the product life cycle in the e-retail industry based on five dimensions of strategic proactiveness, namely customer data analysis, demand forecasting, monitoring market trend, competitor data analysis and real-time analytics and decision support. It also discusses how these dimensions affect the product life cycle phases (product ideas, product development, product launch, product modification/improvement, and product decision – continuation or withdrawal).

Research Problem

Consumer preferences are changing rapidly, the competition is growing, and substitute products launch rapidly in a short time period, all of which are challenges to e-retail businesses. The digital environment has also given customers more opportunities to compare products, prices and ratings, forcing companies to make products quicker to develop, launch, and improve. While these companies have huge amounts of information created when customers purchase products and browse, and they also have data generated when products are used in digital interactions, the issue is not the quantity of data, but its ability to use the data strategically and proactively before market changes or before products are no longer appealing to customers. (Madi، 2026)

Papers related to the subject have shown that big data is useful to formulate marketing strategies, to aid managerial decision making and to boost supply chain performance. The use of it in product life cycle management, however, is still an area of research that needs more investigation, especially in the digital industry where decisions need to be made quickly based on data from real-time information. Bouaissi's study focused on the role of big data in marketing strategy development, and Al-Sharif's study focused on big data analytics in the supply chain management. As opposed to that, the research by Madi was based on the effect of big data analytics on managerial decision making. Although these studies are very significant, they were not specifically directed towards the acceleration of the product life cycle within the e-retail industry. (Al-Sharif ، 2024)

Moreover, the studies dealing with the digital marketing and big data have mostly centered on competitive advantage, marketing performance or customer behavior but not on the product life cycle as a key element of analysis. In the study by Al-Nawaisa, the role of big data as a mediating variable between digital marketing and competitive advantage was discussed, while in Ghattas, the effect of optimal use of big data on strengthening competitive advantage through digital marketing was discussed. On the other hand, the study by Ibrahim showed that there is little research done in the Arab world on big data analytics in digital marketing in contrast to foreign studies. (Al-Nawaisa، 2023)

In the international context, there are significant studies regarding the linkage of big data analytics with proactive market orientation, customer analytics, new product performance and data-driven agility in the retail business. The integrated relationship between strategic proactiveness of big data and the acceleration of the product life cycle (PLCO) has been overlooked in these studies in several aspects, especially in the Arab or Iraqi context. Hence, a research gap arises where there is a need of a study connecting the proactive use of big data and the e-retail sector product-related decisions' acceleration. (Agag et al., 2024)

As can be seen from the above, the research problem of this study is how much are the e-retail companies in Iraq able to use the big data proactively in ways that facilitate the product life cycle, from the first idea and product development, to its launch and modification, and finally to making decisions on its continuation or withdrawal from the market. Therefore, the problem of research is formulated in the following main question:

What is the impact of strategic proactiveness of big data on accelerating the product life cycle in the e-retail sector?

The following sub-questions emerge from this main question:

1. What is the level of strategic proactiveness of big data in e-retail companies?
2. What is the current state of accelerating the product life cycle in the e-retail sector?
3. What is the impact of proactive customer data analysis on accelerating product development?
4. What is the impact of demand and market forecasting on accelerating the launch of e-retail products?
5. What is the impact of monitoring competitors and market trends through big data on improving decisions to modify or withdraw products?
6. Is there a statistically significant relationship between strategic proactiveness of big data and accelerating the product life cycle?

Research Objectives

The study aims to achieve the following objectives:

7. To identify the concept of strategic proactiveness of big data and its dimensions in the e-retail sector.
8. To measure the level of big data utilization in forecasting customer and market trends.
9. To examine the current state of the product life cycle within e-retail companies.
10. To analyze the impact of customer data-driven proactiveness on accelerating product development.
11. To identify the impact of demand forecasting on reducing the time required to launch new products.
12. To determine the impact of proactive competitor analysis on decisions to modify or discontinue products.
13. To provide recommendations that help e-retail companies utilize big data more efficiently in managing the product life cycle.

Significance of the Study

Theoretical Significance: The study's theoretical significance is found in its analysis of a modern and relevant research field, namely the subject of e-retail, which is intertwined with big data, strategic proactiveness and the product life cycle, and is characterised by a dynamic, rapidly changing environment. The study also contributes to enriching the literature related to digital strategic management, data analytics, and product management in the e-commerce environment.

Practical significance: The study's results can be used to make better decisions for e-retail companies regarding product development and launch, pricing, marketing and withdrawing from the market. The results could also aid marketing managers, product managers and data analysts in building more predictive systems and quicker responses to market shifts.

Research Hypotheses

The research hypotheses can be formulated as follows:

Main Hypothesis:

There is a statistically significant effect relationship between strategic proactiveness of big data and accelerating the product life cycle in the e-retail sector.

Sub-Hypotheses:

1. There is a statistically significant effect of proactive customer data analysis on accelerating product development.
2. There is a statistically significant effect of demand forecasting on accelerating product launch in the e-retail market.
3. There is a statistically significant effect of monitoring market trends through big data on improving the speed of product modification.
4. There is a statistically significant effect of competitor data analysis on accelerating decisions regarding product development or withdrawal.
5. There is a statistically significant effect of using real-time analytics on reducing the time required to make product management decisions.

Research Scope

The scope of the study is to examine the effect of Strategic proactiveness of Big Data as independent variable to accelerate Product life cycle as dependent variable. The five dimensions of strategic proactiveness in the use of big data are: customer data analysis, demand forecasting, monitoring market trends, competitor data analysis and real-time analytics and decision support. The product life cycle acceleration is also discussed within five dimensions: Product idea generation acceleration; Product development acceleration; Product launch in the market acceleration; Product modification and improvement acceleration; Product continuation and withdrawal from the market.

The Geographical Scope: The study is carried out in Iraq and taking a sample from employees in e-retail companies and platforms in Baghdad and selected provinces in Iraq.

Human Scope: The study will cover employees of e-Retail companies/Platforms who have any involvement in the research topic including digital marketing employees, product management employees, data analysts, data scientists, information technology employees, e-sales employees, customer service employees, procurement and supply chain employees.

Temporal Scope: The temporal scope of the study covers the year 2026.

Theoretical Framework of the Study

This study's theoretical framework is rooted in the connection of three interrelated fields: big data as strategic digital resources, strategic proactiveness as an organizational competence that requires anticipation and proactive action, and the product life cycle as a managerial and marketing process that is affected by speed of the market and consumers' behaviour. As such, the study does not consider big data as an independent technological solution, but rather as a solution that assists an e-retail organization in speeding up the process of product-related decisions from the idea phase up to its development, launch, adjustment or elimination. In the wake of the recent research that highlighted the increasing interest in big data in digital marketing, the significance of this linkage has risen, given the relative lack of Arab studies that have focused on the issue from the viewpoint of the product life cycle. (Ibrahim، 2025)

Section One: Big Data and Strategic Proactiveness

In the digital business landscape, big data is one of the crucial tools and resources that empowers organizations with a wider understanding and knowledge of their markets, customers and competitors. The importance of data is no longer tied to the volume of data, but to management's capacity to turn data into knowledge that they can use to develop marketing and strategic orientations. The link between big data and proactiveness starts here: The stronger the organization's ability to understand and analyze the data, the stronger its ability to predict the changes that are coming up ahead of time, rather than after they have happened. (Bouaissi ، 2024)

Then, big data becomes a managerial advantage not just because it's available, but because it can be analyzed by an analytical system that can support the decision making process. Descriptive analytics helps to understand what has occurred, predictive analytics aids in an estimation of what is likely to happen in the future, and prescriptive analytics helps direct management to the most suitable choice. This step in analytics is also a crucial building block for strategic proactiveness in that it takes an organisation from data collection to leveraging the data to build forecasts and make decisions early. (Al-Sharif، 2024)

In this context, strategic proactiveness is linked to the capacity of the organization to identify early signs in the external and internal context and turn them into action before they turn into missed opportunities or crisis. In the realm of big data, proactiveness can be seen in tracking customers, studying the competition, analyzing demand, tracking price changes, and measuring the results of digital campaigns. So, big data is no longer just a reporting tool - it's an early-warning system. (Al-Hassan & Saqour ، 2022)

An organization needs the capabilities to support them in using data for proactive action rather than data monitoring. These include the technological infrastructure, analytical software, human skills, organizational flexibility and a management culture conducive to speedy learning. Data is not the source of proactiveness; the organization must be able to interpret, interpret and then link the data to operational and strategic decisions at the right time. (Madi، 2026)

Strategic foresight is the logical step after proactiveness, as it is especially about the future and what future scenarios could be for opportunities and risks. Big data-based foresight is more accurate because it is based on real numbers produced by markets, customers and competitors, not just on general impressions. In this context, strategic proactiveness of big data is an organization's capacity to derive a vision for the future from data to position itself ahead of the competition. (Al-Sharayiah، 2021)

Data and proactiveness would be incomplete without strategic thinking, which can be used to engage with the future as a field of analysis and prediction. Other attributes that enable an organization to make fragmented data strategic are attributes of future-oriented thinking, systems perspective, hypothesis formulation, and intelligent exploitation of opportunities. These are crucial for a fast-paced industry like e-retail, as subtle changes in customer activity can offer clues to significant trends in sales. (Al-Ajaib، 2021)

Strategic proactiveness of big data is a rejuvenated ability to sense change, seize opportunities and reorient decisions and resources based on the data. But data only has a strategic role when it is combined with marketing skills, organization knowledge and quickness to act. This linkage is the first step towards the next section: accelerating the product life cycle, since the ability to read the market and customer behavior must come first. (Brewis et al., 2023)

There are several Arab studies that have dealt with big data in relation to strategic orientation and managerial decision-making. The study by discussed how big data can affect the creation of marketing strategy and the study by discussed the effect of big data on managerial decision making. The research of the group on "Big data and how to improve strategic improvisation using organizational vigilance, agility and memory". These studies help build the foundation of the independent variable for the current study as they have identified big data as a resource that can facilitate decision making and strategic responsiveness. (Al-Hassan & Saqour، 2022)

Other Arab studies have been devoted to the future looking and foresight aspects of data and strategic thinking. The study of Pielke et al. focused on the role of big data in strategic foresight, and the study of Seyyedi focused on the mediating effect of strategic foresight between strategic thinking and organizational excellence. These studies help to explain that strategic proactiveness is not only a rapid decision-making process, but also an ability to think ahead and anticipate and formulate hypotheses and take action in advance. (Al-Sharayia، 2021)

In the foreign literature, however, the connections between big data and innovation, market agility, dynamic capabilities and competitive advantage have been made. Cadden and colleagues' study focused on the use of big data and marketing analytics for innovation and competitive advantage, and Sultana and colleagues' study focused on the effects of data-driven innovation on market agility and competitive performance. The following studies concur that the proactiveness of big data is not limited to the scope of analysis, but also to the development of the organizational proactiveness for innovation and quick reaction. (Sultana et al., 2022)

Section Two: The Product Life Cycle in the E-Retail Sector

Once the subject of big data's role in development of strategic proactiveness has been clarified, it's time to get to the dependent variable: the product life cycle speedup. Product Life Cycle: The stages a product goes through starting with the initial idea, development, introduction to the market, growth, maturity, modification and withdrawal when sales slow down. In the e-retail sector, these stages don't unfold at the same speed as in the traditional markets: customers respond quickly, competitors keep fine-tuning their offerings and substitute products are developed in short timeframes. (Ozdemir et al., 2024)

The product life cycle in e-retail is unique because it is based on real-time data created as a result of the customer's interaction with the platform. Views, click-throughs, product add-to-carats, customer ratings, return rate, comments are all indicators that can help management understand the product's stage in its life cycle. Thus, the product management process model is not just a theoretical one with predetermined stages, but a continuous process that can be monitored digitally and provides insights into the growth rate or decline of a product. (Chen et al., 2026)

While the process of product development is most often driven by market and customer research, the efficiency of the back-end processes that are tied to purchasing, procurement and distribution are equally important. If the organization cannot launch or develop the product at the right time, control suppliers or conduct purchasing, invoicing and payment efficiently, the speed of launching or developing the product becomes of less value. Thus, in the e-retail landscape, the buy-in of marketing and product decisions with a flexible digital supply chain is required to accelerate the product life cycle. (Saleh، 2020)

Demand forecasting is one of the most important factors to shorten the product life cycle as it enables the organization to decrease the time spent on testing the market, focus on categories or seasons that are more likely to grow and better serve the organization's needs, and predict which products are going to perform well. The more an organization can predict the nature and extent of demand fluctuations, the more likely it is to speed up product development efforts to suit the demand, while minimizing the investment in products with less demand appeal. In this instance, the lesson is that faster product life cycles don't require haste, but rather a more informed decision making process, which is executed earlier in the cycle. (Madanchian, 2024)

Digital consumer behavior is also a key determinant of the rate of any product's progression through the stages. In an e-commerce world, people are not just buying products, they are creating data via searching, comparing, rating, commenting, sharing. This information is useful to the organisation for understanding why the product has been accepted or rejected and whether it needs to be altered in terms of price, design, description, or the way it is presented. Therefore, the customer experience is an ongoing source of new product development and a faster decision making. (Theodorakopoulos et al., 2026)

Accelerating the product life cycle is inseparable from innovation as real acceleration can not only be achieved by reducing time, but also by the ability of the organization to develop new product ideas, test them quickly, and develop them to meet the market needs. In the e-retail industry, innovation is more linked to data and the organization can experiment with customer reactions to products and services much faster than in the traditional market. Data-driven innovation is therefore a way of connecting market analysis to the speeding up of the product life cycle. (Dang et al., 2025)

From the above, it is clear that the PLP for e-retail has shifted from being a linear process starting with design and ending with withdrawal, to a dynamic process that can be continuously changed in accordance with data. A product can go to the growth phase quickly, decline quickly and be reintroduced as a modified version of the original product in terms of the features, the way they are presented, or the market segment to which they are aimed. This change bridges the second part with the third part, since strategic proactiveness for accelerating this cycle depends on big data. (Aldossary & Agag, 2026)

There are also a number of foreign studies that have had the focus of understanding the link between customer analytics and the performance of products or e-commerce performance.

Ozdemir and colleagues studied how customer analytics affects the performance of new products; Chen and colleagues studied digital marketing analytics in e-commerce performance in the fashion industry. Both of these studies emphasize that a key role of product management in today's digital world is to act on customer information to drive decisions regarding development, launches and improvement. (Ozdemir et al., 2024)
The link between big data, innovation and agility has been explored in the retail sector in other works. Dang and colleagues' study focused on big data analytics capabilities and sustainable performance of retail companies by innovation, whereas Aldossary and Agag's study was on data-driven agility in retail industry in Britain. These studies highlight the need to innovate quickly and respond dynamically to changes in the market to accelerate the product life cycle. (Dang et al., 2025)
Turning to the Arab studies that are relevant to this section, they have focused on the digital transformation in retail and in supply chains. The study by Saleh is an analysis of how electronic purchasing affects the supply chain performance of retail trade sector in Jordan. This study is useful to the current research in highlighting that accelerating the product life cycle does not depend solely on marketing analytics, but is also associated with the speed of purchasing and procurement and cooperation with suppliers. (2020)

Section Three: The Relationship Between Strategic Proactiveness of Big Data and Accelerating the Product Life Cycle
Once it is understood that big data is strategic proactive and product life cycle in e-retail is unique, it can be seen that there is a relationship between big data and product life cycle that is based on the concept of transforming data into first decisions related to products. Using big data, management can see what items customers want, how their preferences are evolving, and what is gaining or losing in popularity. The timely use of this information can help minimize the time gap between a market shift and the decision to develop, launch, or change a product. (Morimura & Sakagawa, 2023)
The first sign of this relationship can be seen in the product idea generation stage, that is, when big data can help organizations uncover unmet needs or the patterns of new demands before they become a trend. An organization need not wait for the final results of sales to come in before they think of a product; they can use search terms, what consumers are saying about the product, what activity their competitors are doing, and browsing behavior to come up with ideas for a product that better matches what they think people will want. Therefore, proactiveness can be a way to reduce the opportunity identification period at the beginning. (Agag et al., 2024)
The relationship also extends to the product development phase when big data can find out which features are most liked by customers, acceptable prices, the weaknesses of the current products, and gaps in competitors' offerings. If an organization has this knowledge at the beginning then it can decrease the trial and error cycles and create products that are more in line with customer expectations. This translates into proactiveness not only improves decision-making speed, but also the quality of the decision. (Ozdemir et al., 2024)
Data-driven proactiveness is useful in deciding on the right time for the product launch, the most suitable digital channel, and the right target segment that would respond during the product launch. The launch of a product at the wrong time or to the wrong audience can reduce the life cycle of the product from the start of its life cycle in e-retail. So, big data helps the organisation to make more accurate product launches and minimise the risks of a failure in its early stages. (Alghamdi & Agag, 2024)
This working relationship is not complete at launch, it is continued until the monitoring and improvement stage. Once on the market, the product will provide new data on demand, ratings, complaints, returns, and campaign interactions. This data takes the ball up the court to allow for quick decisions on modifications, such as enhancing the product description, price, presentation method or product features. So the acceleration of the product life cycle isn't a "one off" choice but a continuous process. (Theodorakopoulos et al., 2026)
Big data's strategic proactiveness also helps to make better decisions about product retention or withdrawal from the market. If there are signs of problems, the products can be redesigned, re-marketed, decrease the products or get rid of the products that have higher demand. In this

context, data can be used to minimise waste and optimise the product portfolio on the e-retail platform. (Madanchian, 2024)

When big data is integrated with digital marketing, it strengthens this relationship. Digital marketing offers the organization real-time customer information and big data reanalyzes the signals to inform campaigns, products and offers. In e-retail, this integration allows for quick changes to either the product, offer, or target audience, which lessens the product life cycle time lag between the various stages. (Al-Nawaisa، 2023)

Big data also plays a part in optimizing the use of an organization for competing with the market with the help of fast reactions. An early warning organization that swiftly adjusts its offerings is better equipped to keep customers and outflank competitors. The acceleration of the product life cycle is not only an operational goal, but also a means of creating a competitive advantage in a dynamic e-market. (Ghattas، 2020)

Based on the above, the relationship of strategic proactiveness of big data and product life cycle can be seen from three different paths: the first path is the cognitive path, understanding the market and customers; the second path is the predictive path, anticipating the demand and opportunities; and the third path is the implementation path, accelerating decisions on product development, launch, modification, and withdrawal. The interaction between these pathways contributes to making product management more flexible, accurate and quick in the e-retail market. (Ramkumar et al., 2023)

Morimura and Sakagawa's study are focused on the retail sector and focused on the mediating effect of big data analytics capabilities between the market orientation of responsive and proactive and organizational performance. It is one of the foreign studies most directly related to the subject of the current research given that it connects market proactiveness, big data and retail. (Morimura & Sakagawa, 2023)

The study by Agag et al. addressed how marketing analytics, customer agility, and customer satisfaction are longitudinally related in the future, the study by Alghamdi and Agag addressed the role of the data-driven innovation capabilities and marketing agility in developing competitive advantages in the future. In these two studies, it is evident that big data analytics can not only help to speed up decisions regarding products, it also helps the organization to interact with the customer and the market. (Agag et al., 2024)

The study by Ramkumar et al. involves the utilization of big data in e-commerce, thereby directly connecting big data to the context of the present study. This study also supports the theory that ecommerce is leveraging data analytics to gain insights into customers and enhance operational and marketing decisions. (Ramkumar et al., 2023)

Likewise, from the literature review, it is observed that majority of the past research has focused on the management decision making capability, digital marketing, agility, innovation or supply chain management aspects of big data, but the current study proposes to combine these aspects with a single model that analyzes how strategic proactiveness of big data affects the rapid product life cycle in the e-retail environment. This linkage is significant and there is a need for further research especially in the Arab literature, in order to better explore the relationship between big data, digital marketing, and the product life cycle. (Ibrahim 2025)

Research Methodology and Procedures

Research Method

The study employed descriptive-analytical method because it is the most suitable method because the behavior of the study would examine the impact of strategic proactiveness of big data on accelerating the product life cycle in e-retail sector. The way this approach helps describe how e-retail organizations are currently using big data, analyze their strategic proactiveness level and later test the positive impact of big data in the field using data gathered from the sample of participants, is analyzed.

Study Population and Sample

The study population includes employees in e-retail companies and platforms in Iraq, particularly in the departments and units responsible for product management, digital marketing, data analysis, e-sales, customer service, and supply chain. This population was chosen because of its direct relevance to the topic of the study: these groups are daily consumers of customer data, the demands placed on them, competitors, and market trends, and therefore have a better insight into the impact of big data on decisions related to products. The study was conducted on a purposive sample of employees from several e-commerce firms and platforms in Baghdad and some Iraqi provinces, as it is not easy to identify all the employees working in the e-retail sector in Iraq. The sample size, n = 108, is considered adequate for this particular study and type of sample, as it was obtained from those occupations that were most closely related to the study variables.

Table 1. Distribution of the Study Sample Members According to Demographic and Occupational Characteristics

Variable	Category	Frequency	Percentage (%)
Gender	Male	62	57.4
	Female	46	42.6
Age	Under 30 years	35	32.4
	30 to under 40 years	44	40.7
	40 years and above	29	26.9
Educational Qualification	Diploma or below	14	13.0
	Bachelor's degree	76	70.4
	Postgraduate studies	18	16.6
Nature of Work	Digital Marketing and Product Management	32	29.6
	Data Analytics and Information Technology	24	22.2
	E-Sales and Customer Service	28	25.9
	Procurement and Supply Chains	16	14.8
	Senior or Middle Management	8	7.5
Years of Experience	Less than 3 years	28	25.9
	3 to under 7 years	42	38.9
	7 to under 10 years	25	23.1
	10 years and above	13	12.1
Total		**108**	**100**

Study Instrument

The questionnaire was used as data collection tool in the study. The questionnaire was designed in the light of the study variables and their theoretical dimensions. The two sections were: the first was strategic proactiveness of big data, and the second was a measure of product life cycle acceleration, which was the dependent variable. The responses of the respondents were measured using five point Likert scale, which includes Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree.

Strategic proactiveness of big data was measured by five main dimensions: customer data analysis, demand forecasting, monitoring market trends, competitor data analysis, real-time analytics and decision support. Five statements were included for each dimension for a total of 25 statements for the independent variable. These statements aim to assess the potential of e-retail companies to leverage big data proactively and strategically to gain insights into their customers, predict demand, track the market, monitor their competitors and make decisions quickly.

The dependent variable, accelerating the product life cycle had five main dimensions which included accelerating product idea generation, accelerating product development, accelerating product introduction in the marketplace, accelerating product modification and improvement, and accelerating product continuation or withdrawal decisions from the marketplace. A total of 25 statements were given for the dependent variable, five on each dimension. In total, the number of statements in the questionnaire that concerned the study variables was 50, as well as some demographic and work data related to the members of the sample.

Validity of the Study Instrument

The study instrument was tested for validity by displaying the preliminary questionnaire to a group of management, digital marketing, information systems and statistics experts. This was to make the statements clear, good in their wording and material for the dimensions they were related to. Reviewers' comments were incorporated into the instrument by making adjustments to the specific wording of statements and similar statements were either omitted or combined to capture the strategic proactiveness of big data's impact on the acceleration of the product life cycle.

Items' internal consistency validity was also checked by calculating the correlation of the items on each dimension with total score of the corresponding dimension and the correlation of the dimensions with the total score of the main variable. This process is significant as it ensures that the questions are aligned in the direction and that they are in line with the concept being measured.

Reliability of the Study Instrument

To determine the consistency of the respondents in answering the items of each study dimension, the reliability of the study instrument was measured by Cronbach's alpha coefficient. Cronbach's alpha score above 0.70 is statistically acceptable and the nearer the Cronbach's alpha value is to one, the higher the level of internal consistency and reliability of the instrument.

Table 2. Cronbach's Alpha Coefficients for the Dimensions and Variables of the Study

Variable	Dimension	Number of Statements	Cronbach's Alpha Coefficient
Strategic Proactiveness of Big Data	Customer Data Analysis	5	0.88
	Demand Forecasting	5	0.86
	Market Trend Monitoring	5	0.85
	Competitor Data Analysis	5	0.84
	Real-Time Analytics and Decision Support	5	0.89
Strategic Proactiveness of Big Data as a Whole		25	0.93
Accelerating the Product Life Cycle	Accelerating Product Idea Generation	5	0.85
	Accelerating Product Development	5	0.87
	Accelerating Product Launch in the Market	5	0.86
	Accelerating Product Modification and Improvement	5	0.84
	Accelerating Decisions on Product Continuation or Withdrawal from the Market	5	0.83
Accelerating the Product Life Cycle as a Whole		25	0.92
The Instrument as a Whole		50	0.95

It is evident from Table (2) that the Cronbach's alpha coefficients for all dimensions of the study

exceeded the statistically acceptable threshold, ranging from (0.83) to (0.89) for the sub-dimensions. The coefficient reached (0.93) for the independent variable as a whole and (0.92) for the dependent variable as a whole, while the reliability coefficient for the instrument as a whole was (0.95). These values indicate that the study instrument has a high degree of reliability and that its items are appropriate for measuring the study variables in the field.
Statistical Methods Used
The data were analysed with the help of a statistical package for social sciences (SPSS) according to the nature of the study questions and hypotheses. The characteristics of the sample members were described using frequencies and percentages and the tendency of the respondents' answers about the dimensions of the study were measured using the arithmetic means and standard deviation. To get the instrument reliability, Cronbach's alpha coefficient was also used. Pearson's correlation coefficient and simple or multiple linear regression were used to test the hypothesis relationship and effect between the study variables according to the type of the hypothesis.
So, the methodology used was descriptive, analysis and statistical testing to understand the current status of strategic proactiveness of big data in e-retail in Iraq, and to measure its impact on fast product life cycles.

Study Results and Discussion
The results of the study are presented and discussed in the context of the study questions and hypotheses. Descriptive answers to the research questions on the level of strategic proactiveness of big data and on the current situation of the product life cycle acceleration were provided by arithmetic means and standard deviations. The effect related questions and the related hypotheses were tested by correlation and regression analyses. The following criterion was used to interpret the arithmetic means: below 1 to less than 2.34 (low); 2.34 to less than 3.68 (moderate); and 3.68 to 5 (high).
Results Related to the First Question
The first question states: What is the level of strategic proactiveness of big data in e-retail companies?
To answer this question, the arithmetic means and standard deviations of the dimensions of strategic proactiveness of big data were calculated, as shown in the following table:

Table 3. Arithmetic Means and Standard Deviations of the Dimensions of Strategic Proactiveness of Big Data

Rank	Dimension	Arithmetic Mean	Standard Deviation	Score
1	Customer Data Analysis	3.91	0.68	High
2	Real-Time Analytics and Decision Support	3.84	0.71	High
3	Demand Forecasting	3.78	0.74	High
4	Market Trend Monitoring	3.69	0.76	High
5	Competitor Data Analysis	3.55	0.80	Moderate
	Strategic Proactiveness of Big Data as a Whole	3.75	0.63	High

As shown in Table (3), the level of strategic proactiveness of big data in the e-retail companies was high as the arithmetic mean is (3.75) with a standard deviation of (0.63). The dimension customer data analysis came out on top, with an arithmetic mean of (3.91) meaning that the e-retail companies are heavily using customer data to better understand customers purchase behavior, track preferences and analyze how customers respond to offers and products. The competitor data analysis dimension, however, had a moderate level and showed that the companies studied are still not very good at using big data to systematically monitor their

competitors, whereas they are not so good at analysing customers and demand.
This finding is in line with the fact that e-retail organisations in the Iraqi market have started to understand the value of big data in their support of marketing and operational decision making. This recognition seems to be stronger in areas that are more directly related to the direct customer (such as analysing purchasing behaviour and interaction with the platform) than in more complex areas (such as competitor analysis and the development of early-warning systems about competitor movements). This can be attributed to the fact that customer data is usually easier to access in the company's platform or electronic system, while competitor analysis requires more advanced external monitoring tools and analytical skills.

Results Related to the Second Question

The second question states: What is the current state of product life cycle acceleration in the e-retail sector?
To answer this question, the arithmetic means and standard deviations of the dimensions of product life cycle acceleration were calculated, as shown in the following table:

Table 4. Arithmetic Means and Standard Deviations of the Dimensions of Product Life Cycle Acceleration

Rank	Dimension	Arithmetic Mean	Standard Deviation	Score
1	Accelerating Product Launch in the Market	3.82	0.70	High
2	Accelerating Product Modification and Improvement	3.76	0.72	High
3	Accelerating Product Development	3.71	0.75	High
4	Accelerating Product Idea Generation	3.66	0.77	Moderate
5	Accelerating Continuation or Withdrawal Decisions from the Market	3.59	0.81	Moderate
	Overall Product Life Cycle Acceleration	3.71	0.66	High

As seen in Table (4), the overall arithmetic mean (3.71) and standard deviation (0.66) of the product life cycle acceleration for the e-retail sector was high. The dimension of accelerating product launch in the market came out as the first one with an arithmetic mean of (3.82) which shows that e-retail firms have a good capability to launch products relatively quickly in the market via digital platforms. Another dimension, referring to the high rate of product modification and improvement, also reached a high level: Companies benefit from customer feedback, ratings and indicators of demand in order to continually modify the products or their rendering.
The dimension relating to the decisions to take a product off the market or to continue the process has been ranked by moderate level, in contrast. This suggests that businesses can be more likely to be able to create and change products, but less likely to make decisions to discontinue or withdraw products if demand drops. This could be attributed to managerial hesitancy or the fact that measurement systems are not adequate to accurately identify the time at which a product becomes unprofitable or the time at which it should be replaced by another product that is more suited to market needs.

Results Related to the Third Question and Testing of the First Sub-Hypothesis

The third question states: What is the effect of proactive customer data analysis on accelerating product development?
To answer this question, the first sub-hypothesis was tested, which states:
There is a statistically significant effect of proactive customer data analysis on accelerating product development.

Table 5. Results of Testing the Effect of Customer Data Analysis on Accelerating Product

Development

Independent Variable	Dependent Variable	R	R²	F	Sig.	Beta	t	Result
Customer Data Analysis	Accelerating Product Development	0.675	0.456	88.94	0.000	0.675	9.43	Statistically Significant

Table (5) clearly shows that the customer data analysis has a statistically significant effect on the speed of product development, and the correlation coefficient (R = 0.675) and the coefficient of determination (R^2 = 0.456) are all positive. This means that 45.6% of the variance in product development acceleration is accounted for by analyzing the data of their customers. The level of significance (0.000) is lower than level of significance (0.05); thus, the first sub hypothesis is accepted.

The outcome shows that companies with pro-active customer data have superior capabilities to speed up product development, as customer data can give a company early inputs on their preferences, complaints, satisfaction and desired product characteristics. This also minimizes the need to guess or experiment and guides marketing and product lines in making more informed decisions that closely match the needs of the market. Hence, customer data analysis is one of the most important ways that can facilitate the speeding up of the production of new products in e-retail.

Results Related to the Fourth Question and Testing of the Second Sub-Hypothesis

The fourth question states: What is the effect of demand and market forecasting on accelerating the launch of electronic products?

To answer this question, the second sub-hypothesis was tested, which states:

There is a statistically significant effect of demand forecasting on accelerating product launch in the e-market.

Table 6. Results of Testing the Effect of Demand Forecasting on Accelerating Product Launch

Independent Variable	Dependent Variable	R	R²	F	Sig.	Beta	t	Result
Demand Forecasting	Accelerating Product Launch in the Market	0.642	0.412	74.31	0.000	0.642	8.62	Statistically Significant

From Table (6) it is clear that the demand forecasting has statistically significant effect on promoting product launch in e-market. The correlation coefficient was found to be (R = 0.642) and the coefficient of determination was (R^2 = 0.412) suggesting that 41.2% of the variance in product launch acceleration is explained by demand forecasting. The value of the statistical significance level was (0.000) which is lower than (0.05) and accepted the second sub-hypothesis.

This shows that e-retail companies are able to predict demand and make better product launch decisions, find the right target segments to target, determine the number of items that need to be manufactured, and minimize risk of failed product launches. Demand forecasting also reduces the time needed to gauge the market because management receives early indications of products that are more likely to succeed. Therefore, demand forecasting is a crucial tool to move towards the actual product launch from the planning phase.

Results Related to the Fifth Question and Testing of the Third and Fourth Sub-Hypotheses

The fifth question states: What is the effect of monitoring competitors and market trends through big data on improving decisions to modify or withdraw products?

To answer this question, the third and fourth sub-hypotheses were tested, as follows:

Third sub-hypothesis: There is a statistically significant effect of monitoring market trends through big data on accelerating product modification.

Fourth sub-hypothesis: There is a statistically significant effect of competitor data analysis on accelerating decisions to develop or withdraw products.

Table 7. Results of Testing the Effect of Monitoring Market Trends and Competitor Analysis on

Hypothesis	Independent Variable	Dependent Variable	R	R^2	F	Sig.	Beta	Result
Third	Monitoring Market Trends	Accelerating Product Modification and Improvement	0.598	0.358	59.10	0.000	0.598	Statistically Significant
Fourth	Competitor Data Analysis	Accelerating Product Development or Withdrawal Decisions	0.571	0.326	51.30	0.000	0.571	Statistically Significant

It is evident from Table (7) that monitoring market trends has a statistically significant effect on accelerating product modification and improvement, with a coefficient of determination of (R^2 = 0.358). This means that monitoring market trends explains 35.8% of the variance in the speed of product modification. The results also show a statistically significant effect of competitor data analysis on accelerating product development or withdrawal decisions, with a coefficient of determination of (R^2 = 0.326), indicating that competitor data analysis explains 32.6% of the variance in product development or withdrawal decisions. Since the significance level in both cases was (0.000), the third and fourth sub-hypotheses are accepted.

These findings indicate that monitoring the market and competitors represents an important approach to accelerating product-related decisions, as market changes do not emerge solely from within the company but are also reflected in competitor activities, price changes, the emergence of substitute products, and shifts in customer preferences. When a company is capable of continuously monitoring these indicators, it becomes better able to modify a product before its sales decline or make a decision to develop or withdraw it before it becomes a financial or marketing burden.

This finding also explains why competitor data analysis received a moderate level in the descriptive results despite its statistically significant effect. It appears that companies recognize the importance of this dimension but have not yet reached a high level of actual practice in this area.

Testing the Fifth Sub-Hypothesis

The fifth sub-hypothesis states:

There is a statistically significant effect of using real-time analytics on reducing the time required to make product management decisions.

Table 8. Results of Testing the Effect of Real-Time Analytics and Decision Support on Reducing the Time Required for Product Management Decisions

Independent Variable	Dependent Variable	R	R^2	F	Sig.	Beta	t	Result
Real-Time Analytics and Decision Support	Reducing the Time Required to Make Product Management Decisions	0.621	0.386	66.67	0.000	0.621	8.16	Statistically Significant

It is evident from Table (8) that real-time analytics and decision support have a statistically significant effect on reducing the time required to make product management decisions. The correlation coefficient was (R = 0.621), while the coefficient of determination was (R^2 = 0.386), indicating that real-time analytics explain 38.6% of the variance in the speed of product management decision-making. The statistical significance level was (0.000), which is lower than (0.05), indicating that the fifth sub-hypothesis is accepted.

This result indicates that the availability of real-time data, dashboards, and real-time analytics helps management reduce the time between the emergence of a problem and the decision-making process. In the e-retail sector, important indicators may emerge within a short period, such as declining demand, increasing returns, rising complaints, or reduced engagement with a particular product. The faster these indicators become available to management, the more quickly decisions can be made regarding product modification, improvement of its presentation, repricing, or withdrawal.

Results Related to the Sixth Question and Testing of the Main Hypothesis

The sixth question states: Is there a statistically significant relationship between the strategic proactiveness of big data and the acceleration of the product life cycle?

The main hypothesis also states: There is a statistically significant effect relationship between the strategic proactiveness of big data and the acceleration of the product life cycle in the e-retail sector.

Table 9. Correlation Coefficient between Strategic Proactiveness of Big Data and Product Life Cycle Acceleration

First Variable	Second Variable	Pearson Correlation Coefficient	Significance Level (Sig.)	Result
Strategic Proactiveness of Big Data	Product Life Cycle Acceleration	0.781	0.000	A Statistically Significant Positive Relationship

It is evident from Table (9) that there is a positive and statistically significant correlation between the strategic proactiveness of big data and product life cycle acceleration, with a correlation coefficient of (0.781), which is a relatively high value. The significance level was (0.000), which is lower than (0.05). This indicates that as the level of strategic proactiveness of big data increases in e-retail companies, the level of product life cycle acceleration also increases.

To determine the effect of the dimensions of strategic proactiveness of big data collectively on product life cycle acceleration, multiple regression analysis was employed, as shown in the following table:

Table 10. Results of Multiple Regression Analysis of the Effect of the Dimensions of Strategic Proactiveness of Big Data on Product Life Cycle Acceleration

Independent Variables	Beta	t	Sig.	Result
Customer Data Analytics	0.241	3.18	0.002	Statistically Significant
Demand Forecasting	0.222	2.86	0.005	Statistically Significant
Market Trend Monitoring	0.176	2.31	0.023	Statistically Significant
Competitor Data Analytics	0.159	2.08	0.040	Statistically Significant
Real-Time Analytics and Decision Support	0.268	3.54	0.001	Statistically Significant
R	0.781			
R^2	0.610			
Adjusted R^2	0.592			
F	31.96		0.000	The Model Is Statistically Significant

It is evident from Table (10) that the multiple regression model is statistically significant, with an F-value of (31.96) and a significance level of (0.000), which is lower than (0.05). The coefficient of determination was (R^2 = 0.610), indicating that the dimensions of strategic proactiveness of big data collectively explain 61% of the variance in product life cycle acceleration, which is a relatively high explanatory percentage in management studies.

It is also evident that all dimensions of strategic proactiveness of big data had a statistically significant effect on product life cycle acceleration. Real-time analytics and decision support ranked first in terms of effect strength, with a Beta value of (0.268), followed by customer data analytics with a value of (0.241), demand forecasting with a value of (0.222), market trend monitoring with a value of (0.176), and finally competitor data analytics with a value of (0.159). This indicates that product life cycle acceleration does not depend on a single dimension but is influenced by the integration of several analytical and strategic dimensions.

This result indicates the acceptance of the study's main hypothesis, namely, that there is a statistically significant effect of strategic proactiveness of big data on product life cycle acceleration in the e-retail sector. This can be explained by the fact that the product life cycle in the digital environment has become largely associated with the speed of obtaining and analyzing data and transforming it into decisions. Companies with greater capabilities in customer analytics, demand forecasting, market monitoring, competitor data analytics, and the use of real-time analytics are better able to accelerate the generation of product ideas, develop and launch products, modify them, and make timely decisions regarding their continuation or withdrawal.

Summary of the Study Results

The results of the study showed that the level of strategic proactiveness of big data in e-retail companies was high, and the level of product life cycle acceleration was also high. The results of hypothesis testing demonstrated a statistically significant effect of customer data analytics, demand forecasting, market trend monitoring, competitor data analytics, and real-time analytics on the dimensions of product life cycle acceleration. The results also revealed a strong positive correlation between strategic proactiveness of big data and product life cycle acceleration, and that the dimensions of strategic proactiveness collectively explain a high proportion of the variance in product life cycle acceleration.

Accordingly, it can be concluded that big data does not merely represent a technological tool in the e-retail sector; rather, it represents a strategic capability that helps companies reduce decision-making time, improve the quality of product management, and respond rapidly to changes in the market, customers, and competitors.

Recommendations

In light of the findings reached by the study, the following recommendations can be presented:

1. The first step of using big data in the management of product decisions in e-retail companies in Iraq should be oriented in a strategic direction rather than limited to a descriptive report and anticipate changes in customer behavior and market trends.
2. Companies should improve their capacity to continuously analyze customers' data, e.g. monitor browsing, buying, product ratings, customers' complaints, returns, and interactions with offers, and directly feed this data into product development and improvement.
3. In e-retail sector risk of shortage of products or too much and unwanted products should be reduced through development of demand forecasting system so that companies would be able to know which product is in greatest demand, what is the right time to launch a product and what quantity of the product should be stocked.
4. Market trend monitoring systems should be established on a regular basis that will monitor and track shifts in customer preference, trending products, prices, seasons, digital transformation in consumer behavior, etc., and should be used to get the product modified or re-introduced in a timely fashion.
5. More focus should be directed towards competitor data analytics, which is the least practiced dimension and involves monitoring the competitor's prices, offers, product ratings, marketing strategies and strengths and weaknesses of their products, as it contributes towards understanding the competitor.
6. Management should adopt real-time dashboards to help them make product management decisions based on direct data on sales, demand, inventory, customer satisfaction, return rates and product performance indicators, which could help them save time in making

product development, modification or withdrawal decisions.

7. When the product reaches the next stage of the product life cycle, the outcomes of digital analytics should be aligned, with measurable quantitative data points helping to guide the transition, for example from product development to launch, from launch to modification, from decline to withdrawal from market.
8. Digital marketing professionals, product managers, data analysts, and supply chain staff should be equipped with the skills to utilize big data analytics tools, which will improve their comprehension and utilization of digital indicators and translate them into swift, actionable choices.
9. The integration and collaboration among the various departments within the company should be improved, especially in the case of the marketing, data analytics, sales, customer service and supply chain departments, as the PL cycle can't be accelerated by one department in isolation and needs to be continually coordinated across the entities that create data and the entities that use it for decision-making.
10. The e-retail firms should form dedicated market intelligence and data analytics departments or teams to keep a track of the signals of opportunities and threats and make forward-looking decisions on products and offerings.
11. Predictive and prescriptive analytics should be encouraged within e-retail businesses, especially when deciding on new product introduction, price optimization, managing digital campaigns, and enhancing customer experience.
12. Senior management need to focus more on building a data-driven decision making culture, supporting digital transformation, giving them the right software and getting them to use data to understand the problem and come up with solutions.

Suggestions for Future Studies

1. Conduct a comparative study between e-retail companies in Iraq and other Arab countries to measure the difference in the use of big data to accelerate the product life cycle.
2. Explore how AI and predictive analytics can enhance new product development decisions within the e-commerce industry.
3. Analyze how Big Data Analytics can impact Product Life Cycle by analyzing the intervening mechanism, which is marketing agility.
4. Analyze how competitor data analytics can help e-retail firms to create competitive advantages.
5. Do a qualitative study to understand the qualitative aspects of using big data for product related decision making by interviewing product managers and data analysts.

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