Rationalizing the Costs of Short Life-Cycle Products in a Dynamic Business Environment Using Artificial Intelligence Forecasting Techniques and Dynamic Quality Function Deployment – Empirical Study

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Abstract

The life cycle of the products doesn't have the same length in all types of products but there are some long term and medium term products. Due to the rapid growth and the quick innovation of the industry, the life cycle of some products has been shortened resulting what's known as "The short life-cycle products". The short life-cycle products are those products with a life cycle between three months and one year, mostly are the fashion based and technology based products. In order to reach the desired cost rationalization, the organization should focus only on eliminating or minimizing the waste as any arbitrary cutting of the costs would result a declining in the quality of the products. It was proposed by this paper to use the dynamic quality function deployment which relies on designing the products according to specific attributes and costs which is doable in case of having an accurate insight in the whole cost structure of the entire value chain of the product. A matter like that requires a huge amount of data to be collected which is only applicable using AI tools. As the SLCPs have a unique nature which limits the organization ability to collect historical data of these products due to its novelty, the demand of these products is very much uncertain, a matter which hinders any cost rationalization attempt. Accordingly, it was proposed to use the machine learning technique as an AI predictive tool that supports both demand and cost estimation of these newly introduced products.

Keywords: Cost rationalization, Short life-cycle products, Artificial intelligence (AI), Dynamic quality function deployment (DQFD), Forecasting techniques, Demand Enhancement.

Introduction

Recently, due to the dynamic business environment caused by rapid growth and some environmental and ecological variables, new products are introduced continuously whether in the shape of entirely new products or in the shape of re-manufactured products with different attributes as, enterprises are trying to reuse, remanufacture and recycle its current products in order to submit it again to the market with different attributes, sometimes for the same use but with better or newer capabilities and some others for a different usage. A matter like this had shortened the life cycle of the products.

As a result of the previous, a new type of products has recently showed up in the global markets which called the short life-cycle products. These short life-cycle products are characterized by rapid growth, maturity, and decline phases. These short life cycle products have arisen a great level of uncertainty regarding the cost recording, cost rationalization and market demand to these products because of its unusual nature and characteristics. These uncertainties may complicate the point of cost recording, cost analysis and then will make it difficult for any effort of cost rationalization and cost reduction. Accordingly, it was thought that this unique nature of products requires a new approach of cost rationalization that can keep up with the dynamic nature of these products.

It was noted that, one of the major problems associated with the short life cycle products is the uncertainty of demand and costs throughout the value chain of these products. Accordingly, an accurate forecasting technique is a must in order to anticipate the costs and also the demand of the products. Gladly, artificial intelligence nowadays has introduced set of forecasting techniques which have proven its accuracy over time.

Research Problems:

For any forecasting technique to be applied or used to anticipate the costs associated with the production of this type of products and even to anticipate the demand of these products, a historical cost and sales data are required as an inputs to the forecasting system as, the demand history of products can provide valuable information on the shape of the demand curve. Unfortunately, in this particular case of the short life cycle products, there is a significant lack of historical data as it's a newly introduced product with no history in the markets before. Also, any significant time series of the product's own historical data is not available until very late in its life cycle. This implies that initial forecasts of both costs and sales must be generated on the basis of other information.

The short life cycle nature of these products whether it is upgraded, or entirely new product lines has resulted not only a demand uncertainty, but also cost uncertainty as the procurement costs are very much uncertain and very difficult to be anticipated regarding its novelty. Also, as a result of the demand uncertainty it's very difficult to decide the amount of production and accordingly the amount of materials and parts needed for the production, knowing that the major components of the production consume a large portion of the product's entire life cycle and over such a long horizon, the trend in demand is likely to change significantly. The decision of how much to purchase? and when to purchase? are very critical questions needed to be answered in order to be able to control the procurement costs.

As, most of the component parts of the production represent a new technology that have just introduced, another problem regarding the procurement costs have arisen from the volatility in component prices. Also, the market prices for the major components decline significantly over a short time. Therefore, the cost of keeping inventory is very significant in the competitive market. In view of this, the accuracy of projections is critical to maintaining a cost-conscious procurement plan.

Research objective:

This research aims to reach a new approach to rationalize the costs of the short life-cycle products through an integrated framework of an accurate artificial intelligence forecasting tool and the dynamic quality function deployment model.

Plausibility of the research:

The current study represents one of very few studies which prepared to discuss the problem of the short life-cycle products. The main advantage of the current work is the attempt to plan for an integrated cost rationalization framework which is not only attempts to point out the different components of the short life-cycle products' cost, but also to achieve the rationalization at the same time for this type of products.

Research limitations:

The research paper will focus on examining the newly introduced artificial intelligence forecasting techniques along with the application mechanism of the dynamic quality function deployment in an integrated framework in order to reach the most appropriate approach to rationalize the costs of the short life-cycle products.

Research Hypotheses:

Different hypothesis will be tested within the context of this work as: -

H1: There is a statistical relationship between the adoption of the dynamic quality function deployment model and demand enhancement.

H2: There is a statistical relationship between demand enhancement and cost rationalization.

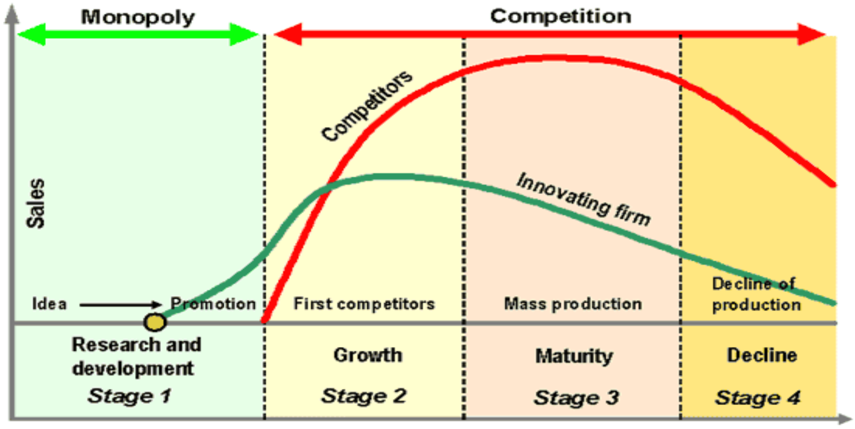
H3: There is a statistical relationship between the accuracy of demand forecasting and cost rationalization.

1. Short life cycle products and their consequences:

The stages through which individual products develop over time is commonly termed as, 'Product life cycle'. Alternatively, we could also refer to product life cycle as the time between the first introduction of the product to the market and the time at which the product loses its potential to generate profits due to newer products or newer technologies thus inducing obsolescence. A product life cycle is commonly divided into four stages all over the value chain of the product; Market development, market growth, market maturity and market decline stages (Levitt, 1965). Figure 1 depicts a typical product life cycle.

Due to rapid introduction of newer and better products which emerge from newer technologies the product life cycle has shortened over time. The industry has been for a while pummeled with the shortening of the product life cycle. It has introduced obsolescence of the existing products which has grown into market competition and a tremendous squeeze on profits (Goyal, 2021). Shortening the product's life cycle is not only due to the obsolescence of demand but also due to the deteriorating nature of these products as deterioration is defined as decay, damage, spoilage, evaporation, obsolescence, pilferage, and loss of entity or loss of marginal value of a commodity that results in decreasing usefulness from the original one, so a product which deteriorates rapidly is called a short life cycle product (Chung and wee 2011).

Figure (1): Product Life Cycle



Source: (Paul, 2018).

Products with life cycles of a few months to a maximum of 3 years are called short life-cycle products which are very common in fashion-based (e.g., toys and clothing) and high technology (e.g., computers and consumer electronics) industries (Kurawarwala and Matsuo 1998).

Short life cycle product is an item that is typically not intended to be a replenished item or is an item that is in a time period during which replenishment systems cannot forecast demand appropriately. Short life cycles are typically encountered in two kinds of products: innovative products such as electronic goods and fashion goods which have a seasonal demand pattern built into perishable goods which due to their very nature have a very short shelf-life. There are two reasons which contribute to the short life cycle – first, these products normally have a high turnover of seasonality. Second, due to the high rate of profitability a firm can attain in a short period of time due to the high new product turnover rate. (Paul, 2018).

(Chen & Xu, 2001) stated that, the short-life-cycle products, or perishable products, experience introduction, growth, maturity, and decline stages very quickly. Demands for such products are also very unstable etc. (Zhao, et al., 2014).

The Dumping and Countervailing Duty Provisions in the Omnibus Trade and Competitiveness Act of 1988 stated that "Short life-cycle products are defined as products that are state-of-the-art technology for a period of less than four years. The provision provides that a petition must be filled with the ITC by a member of the domestic industry in order to designate a product category as short life cycle. The petition must establish the existence of a short life-cycle product category and demonstrate that there have been at least two dumping orders in a product category with estimated duties of at least fifteen percent" (Zain, 2016).

From all of this, it was though that we could also define the short life-cycle products as the products with a short time between introduction phase of the product in the market and the time at which the product loses its potential to generate profits due to newer products or newer technologies thus inducing obsolescence.

1.1 Characteristics of the Short Life-cycle products:

The characteristics of short life cycle product which are different from those of ordinary product are listed as follows (Gustavo, 2022):

Lack of historical data.

Notable product demand data is not available, because the life of product is vanishing as long as there is a significant reduction of demand in market. This shows that the initial forecast information must be gotten through other channels because enough forecast information is hardly available (Gustavo, 2022).

Deteriorating Inventory.

There is much more study on visible deteriorating than invisible deteriorating. The physical perishable product would be quite different from its original product once it has changed. The decrease of its value is not due to the change in the market value, but due to the changes of itself such as rot and volatile. Decay rate of short life cycle product is essentially obsolete, which is invisible. The decrease of the value of product is attributed to the change in market. In the high deteriorating situation, the same stocks will inevitably bring about high costs. In order to reduce inventory loss, higher accuracy is needed for prediction (Gustavo, 2022).

The dynamic of new products demand is generally characterized by a relatively slow growth in the introduction stage, followed by a stage of rapid growth, afterwards the demand is stabilized, and the product enters in a stage of maturity; finally, the demand declines and then, the product usually is replaced by another product (Trappey & Wu, 2018; Meade & Islam, 2016).

This phenomenon is motivated by a continuous introduction of new products as a consequence of highly competitive markets. In this context, the competitive advantage of a company is determined largely on its ability to manage frequent entries and exits of products (Wu et al., 2009).

Longer lead time.

Owing to the fierce market competition, enterprises have to take account of all aspects of production in order to reduce cost. In the process of procurement, early mass purchasing can get the benefits of purchasing discounts, deferred payments and other cost advantages. As the time of delivering orders, supplier's production and delivering is long, the lead time of procurement will be longer. Thus, in order to response the need of customer quickly, enterprises often have to purchase in advance. For example, the procurement lead time of computer chips or monitors is six to nine months. Lead time will affect inventory levels, the flexibility as well as service level. Longer lead time makes forecast-driven activities inevitable together with more uncertainty (Xianhao & Oizahi 2017).

This type of products is also difficult because high technology and investment usually is required, the manufacturing and distribution lead times are usually long, and the risk of excess or shortage of inventory during the life cycle is high (Rodriguez & Vidal, 2019).

Strong uncertainty of demand.

Short life cycle products are usually generated in intense competition industry. It became apparent that uncertainty of the demand of product with short life cycle is stronger than that of other type of product. The reasons are caused by relatively mature industry, market changes, competitor strategies, internal emergencies, suppliers and so on. In the situation of uncertain demand, mixed-mode with dynamic random fluctuations makes difficulties in forecasting (Xianhao and Qizahi, 2017).

Short life cycle products (SLCP) are characterized by a demand that only occurs during a short time period after which they become obsolete1, this leads in some cases to very short demand time series and the period of demand can vary from a few years to a few weeks as can be seen in the Colombian textbook industry (Rodriguez & Vidal, 2009)

The demand of a SLCP is highly uncertain and volatile, particularly in the introduction stage (Wu & Aytac, 2010). Additionally, the demand pattern is transient, non-stationary and non-linear (Rodriguez, 2019).

Multi-product environment.

If the product is independent and meet special needs respectively, the forecast for individual product can get better results. However, as to the short life cycle products, many of them have the same core functions. An individual strategy of product will affect the demand of other products (Xianhao and Qizahi, 2017).

From all these, the researcher can conclude that the Short life-cycle products have the following distinct characteristics (Paul, 2018):

- Capricious demand patterns.
- High rate of obsolescence.
- Risky capacity decisions and high levels of uncertainty at all levels of operations.
- The selling season is relatively short with a well-defined beginning and end.
- The demand to a large extent has to be decided prior to the start to the selling season.
- Forecasts have to be generated prior to the selling season by taking into consideration of the inactive (no sales) period between the selling seasons.
- Short life cycle products are often substitutable, and customers would replace the products based on the availability.
- The economic conditions or the customer choice considerations may have changed during this period.
- Sales of short life cycle products are usually influenced by promotional activities that extend during the selling season.
- Delivery lead times for major components could be as long as the product life cycle.
- Costs of key components decline over time.
- Cost of obsolescence is very high and fast and timely delivery of customer's order is crucial to competitiveness.

Large procurement lead times.

The lead times for major components such as microprocessors, memory chips, and displays range from 6 to 9 months. That covers a large portion of the product's entire life cycle. Over such a long horizon, the trend in demand is likely to change significantly, and the forecasting method must be able to anticipate such a change.

Volatility in component prices.

The market prices for the major components decline significantly over a short time. A 30% change in motherboard prices over a 3- to 4-week period is not an uncommon occurrence. Therefore, the cost of keeping resource inventory is very significant in the competitive PC market. In view of this, the accuracy of monthly projections is critical to maintaining a cost-conscious procurement plan. Accurate monthly forecasts require accurate projections of seasonal variations in demand.

1.3 Forecasting the demand of short life cycle products

There are different situations that make complex demand forecasting of short life cycle products. On one hand, the time series of demand of such products appears to be non-stationary, non-linear, and transient another problem related to the demand forecasting of short life cycle products is the scarcity of historical data. These products once introduced to the market have a short period of sales. Then, there are little or no historical information related to the sales of such products. These are a severe inconvenience because in spite of the existence of forecasting methods for non-linear time series, such these techniques generally require large amounts of data in order to obtain accurate forecasts. Many non-linear models have been proposed in the field of time series analysis. This models, in the same way that linear models, requires large amount of data to obtain accurate results (Paul, 2018). Furthermore, the proposed nonlinear models employ explicit parametric forms; however, it is usually hard to justify a priori the appropriateness of such explicit models in real applications. The use of non-parametric regression analysis (such as support vector regression and artificial neural networks) can be an effective data driven approach (Triana, 2012).

The traditional short- to medium-term demand forecasting methods are not oriented toward forecasting of short life cycle products. In many of these methods, the long-term (long-term trend, cyclical component) and the short-term (seasonality, short-term trend) patterns are considered distinct and treated separately, one point of difficulty may appear here regarding the elaboration of the same quantitative models. Indeed, decomposition methods are designed to identify and separate the time series into its various components. Smoothing methods such as moving averages, simple and linear exponential smoothing, and related approaches are best applied to steady trends (Kurawarwala & Matsuo 1998). Smoothing methods perform well only when the trend is stable over the short term. For these methods, a change in trend usually leads to a systematic lag or lead effect. Therefore, in forecasting applications for short life cycle products that undergo rapid growth, maturity, and decline along with seasonal variations, simple smoothing methods have definite drawbacks. In short, these traditional methods are not designed for application in the short life cycle environment. More sophisticated time series methods, such as decomposition and the Box-Jenkins models, require many data points for proper identification and parameter estimation. A sufficiently long time series is not available for short life cycle products until the end of their life cycles (Kurawarwala & Matsuo 1998) & (Patil, et al ,2010).

The issue of the perfect or almost perfect order quantity that responds to the market demand is closely related to firm's profits as "The classical single period problem SPP is to find a product's order quantity that maximizes the expected profits under probabilistic demand. The SPP model assumes that if an inventory remains at the end of a period, a discount is used to sell it or it is disposed of (Khouja ,1999).

Very short life cycle products such as fashion and seasonal products have life cycle ranging between 3 and 6 months (Sen, 2008; US Office of Technology Assessment, 1987), and these products exhibit high demand uncertainty before their launch. In the past, firms that procured and sold such products to end customers or retailers usually ordered the entire order quantity well before the selling season due to the demand uncertainty, the short lifespan and quick obsolescence of the products, the difficulties in repeated negotiations and procurement, and the long procurement lead time. Depending upon how the products performed the original forecast, the firms used to incur mismatch costs due to either short supply or surplus supply. Since the last decade, these firms have been using quick response strategies to reduce the mismatch costs for such products (Fisher and Raman, 2001). The initial business volume could be between 60% and 100% of the total anticipated order (Subrahmanyan, 2000). For example, suit buyers procure 80% before season, keeping the remaining 20% of the budget back until after the season starts.

Though the demand for the product is highly uncertain and unpredictable at its launch, it becomes more predictable after an analysis of the early demand pattern (Fisher and Raman, 1996). The quick response supply chains research stream used this more refined demand information and suggested some sourcing strategies by representing the resulting problem as a two stage stochastic program (Fisher and Raman, 1996; Bradford and Sugrue, 1990).

2. Quality function deployment Versus Dynamic Quality function deployment:

Quality Function Deployment (QFD) started in Japan as a quality system focused on providing goods and services that satisfy the desires and requirements of customers. In order to provide value to customers efficiently, it is critical to listen to the voice of customers at every phase related to the development of products or services. Yoji Akao, Shigeru Mizimo and other quality experts in Japan have developed quality function deployment (QFD) models by developing a comprehensive quality assurance system to meet customers' desires with new products and services. Since 1983, companies have used quality function deployment (QFD), by presenting cross-functional teams and concurrent engineering to improve their products and services as well as design and develop their procedures (chaoqun, 2010).

QFD is a comprehensive concept that provides the methods used to translate customer needs into the technical Attribute (TA) For each phase of production and product improvement and take into consideration the cost when studying the House of Quality (HOQ), it is also a cost rationalizing model in the product design phase (Jariri and Zegordi, 2008).

QFD is a powerful model in which the customer's voice is heard throughout the product design process, the key philosophy of using QFD is to apply quality requirements to the customer at different phases of product design, so all specifications and the features that customers need to take into consideration when designing products (Karimi and Jafari, 2014).

Thus, the QFD is a Customer-Oriented Model by developing products and services that satisfy and meet customer needs and Priorities, helps guide management towards reaching new products, QFD encourages management to understand the desires and needs of its customers which leads to increase their ability to compete in the markets, It can be considered as the visual and audio language through which the customer's desires are heard and responded to and translated into technical advantages and properties to optimize the quality of production and to provide the final product in a means that satisfy customers priorities and requirements (Abu-Dahab, 2021).

In addition, the QFD optimizes the quality of the product, helps to determine the order of priorities of customers that they need in the product or service and work to achieve high quality compared to competitors and at the same time at a lower cost which leads to rationalize cost and Allows companies to increase their ability to compete in the market and to realize a greater competitive advantage for the company (Abu-Dahab, 2021).

QFD is one of the models of quality management systems Which are used to satisfy customer requirements and needs those requirements to improve their satisfaction by working on product development and production processes, and the philosophy of the quality function deployment (QFD) is based on determining the standards that must be taken into account to meet the quality requirements and define them within products that must begin early in the product life cycle, The quality function deployment (QFD) involves the following four phases : (1) House of Quality (HOQ), (2) parts deployment, (3) Process planning, (4) Production planning (Chan and Wu, 1998; Rajiv, et al, 2014; Singh and Kumar, 2014;Yan et, al, 2022).

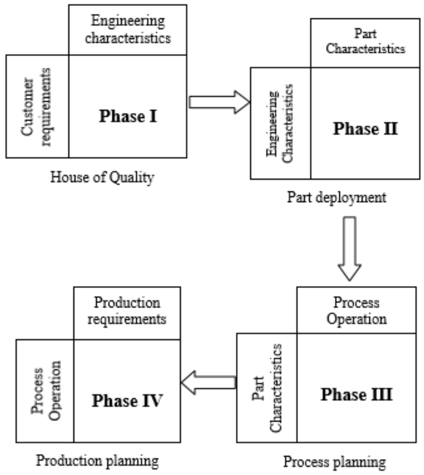
Phase I- The first phase of QFD is Formulating the "House of Quality (HOQ)", in this phase, customer requirements and priorities (WHATs) are taken into consideration and accordingly, translated into engineering characteristics (HOWs) in order to make sure that, the intended product would be at customer's expectations.

Phase II- QFD second phase is the actual deployment of production materials and parts or the needed components of the product, which fulfill the engineering characteristics determined in the - new WHATs.

Phase III- Process planning, this is the phase in which the key component parts (new WHATs) are used to design the production operations (HOWs) which is how to use these parts to produce a product with previously determined characteristics. During this process planning, manufacturing processes are documented in flow charts and target values.

Phase IV- Finally This phase helps the company to develop a correct action plan to ensure efficiency and effectiveness operations. This phase could represent the follow up phase. In order to follow the requirements and needs of customers from the beginning of the product planning process through the operational level, QFD uses a nested structure to link goals and means at each phase, the following figure 2 shows the phases of the quality function deployment (QFD):

Figure (2): Quality Function Deployment: four interlinked phases.



Source: (Chan and Wu, 1998)

The process of converting customer requirements and needs into technical specifications of the product can be summarized as shown in the previous figure. It shows how to translate customers' needs into engineered specifications and technical characteristics, then transforming the attributes and characteristics into operational processes to ensure that the final product is delivered in a way that meets customer expectations at the lowest possible costs. (Abu-Dahab, 2021).

2.1 Constructing the House of Quality (HOQ):

As the “House of quality (HOQ)” is the first phase of the any QFD system. The purpose of HOQ is to translate customer needs and desires into product design specifications (referred to in QFD terms as “Engineering Characteristics”). HOQ shows what customer needs and how designers achieve the requirements in product development phase. It provides a framework and guides the designer to set the target to improve their product quality (Singh and Kumar, 2014; Moubachir and Bouami, 2015).

In order to quality function deployment (QFD) analysis, a matrix of HOQ is used to organize and identify the interrelationships between customer requirements (referred to as "WHATs") and the Engineering characteristics (referred to as "HOWs"), And this matrix summarizes information about the main technical characteristics that must be present in the product and related to the order of priorities of customers and the interrelationship between those Engineering characteristics, Construction of house of quality requires six steps Represented in (Adiano and Roth, 1994; Chan and Wu, 2005; Annappa and Panditrao, 2013; Albalawi, 2014; Singh and Kumar, 2014; Erdil, 2019):

Step I: Develop a list of customer requirements and specify the importance of each of these requirements.

Step II: includes market data, develop a strategic goal for new products and prioritize customer requirements.

Step III: includes information that helps translate customer needs into technical features or engineering features.

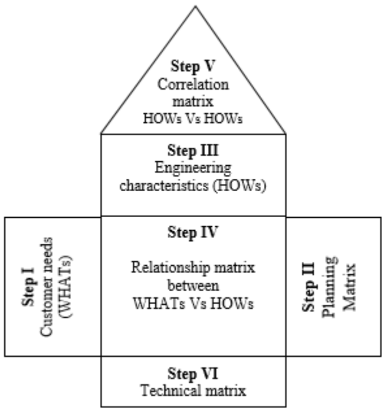
Step IV: contains the relationship matrix between each customer's requirements and each engineering features required in the product.

Step V: the roof of HOQ to measure the correlation matrix between the engineering features and characteristics.

Step VI: includes information to prioritize engineering characteristics, information about competitors and technical goals.

The following figure 3 shows the steps to Construction of House of Quality (Six HOQ steps)

Figure (3): House of Quality (HOQ), description.



Source: (Chan and Wu, 2005)

Finally, the House of quality works to help both engineers and technicians identify several of the engineering advantages and specifications that develop product performance, and also help the design team in the targeted improvements that must be made to the product in order to rationalize costs of the product without compromising quality (Abu-Dahab, 2021).

2.2 Criticisms regarding the traditional Quality function deployment

Due to the limitations of the traditional model had strategic post-design implications. The traditional QFD model resulted in better primary product designs; e.g. fewer start-up problems, fewer design changes and shorter product development cycles.

Although the traditional model is an essential step, it fails to adequately deliver a holistic and dynamic view of customer needs across the value chain elements. For instance, manufacturers continuously ship products without considering the complex relationships between customer satisfaction and product, service, and supplier quality.

Taking a holistic, longer-term view, it is better to update dynamically the process and product parameters based on attributes that are important to customers.

Since traditional QFD model is oriented towards product and process planning; it lacks a continuous focus to improve customer satisfaction over the product life cycle which leads to rationalize the costs of products without compromising quality (e.g. after the initial design is completed) (Nikseresht, et.al, 2024).

A major problem remains: how can the company narrow the gaps created by QFD applications? By incorporating a feedback loop from customers to manufacturers, designers, suppliers, and after-sales service, the company has the opportunity to monitor the changing pulse of the customer, and thus, fine-tune important products and process parameters routinely. For those parameters requiring significant changes, the system-exposed product features are fed back to the designers for the next product release. Systematic capture of customers' experience with the product can produce invaluable market and process research information to be exploited for future competitive advantage. For example, researchers have proposed the coupling of QFD and statistical process control (Scheurell, 1993).

In SPC, the primary main is to build the product right the first time. The primary main of QFD is to specify both the product and process correctly from the outset…Furthermore, QFD may bridge a gap between customer-driven specifications and concurrent engineering.

3. Insights of Dynamic Quality function deployment (DQFD):

Through the combination of dynamic quality function deployment and statistical process control on basic process parameters, dynamic QFD became a critical model for optimizing manufacturing capabilities. Managing the manufacturing interface with other functions and with value chain partners can potentially coding years of problem-solving experience and problem-solving information, whereby a significant degree of functional engineering knowledge is transferred to the production worker. Thus, workers' abilities to control their own processes are enhanced. Moreover, the historic process data obtained from process monitoring can be utilized for continuous process improvement, and when necessary, for re-engineering processes that aren't correspond of strategic alignment with advanced customer priorities (Adiano & Roth, 1994).

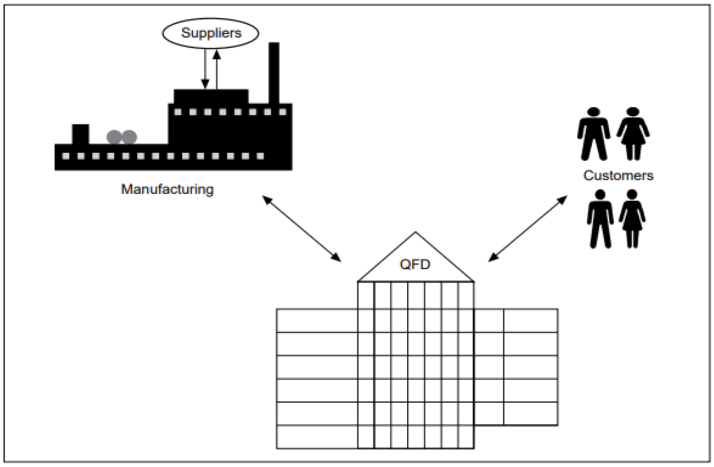
From a strategic perspective dynamic model to QFD enhance the company's ability to reach six sigma quality more effectively and efficiently, and therefore, to provide high value-added products and services. At the same time, the technical and managerial experts are free to work on innovations, experiments, and other innovative solutions required in a competitive global economy. In the future, as more information is captured, analyzed, and aggregated, dynamic QFD will become a broader-based strategic decision-aiding model (Adiano & Roth, 1994).

Dynamic QFD obtains customer input in both the product design and production planning, and through customer comments guides further product and process development. This serves to increase the rate of improvement in the quality of products shipped.

Dynamic QFD sensitizes employees and managers to changing customer desires and requirements. It is however, more than a model for continuous improvement. Dynamic QFD motivates further process and product innovations. For example, what if products did not exist for "updated" customer needs and wants? To answer this question heightens employer sensitivity towards innovation and breakthrough thinking that drives manufacturing and supplier processes towards providing high-value products to the market.

The following figure 4 shows the Conceptual Model of Dynamic QFD

Figure (4): Conceptual Model of Dynamic QFD.



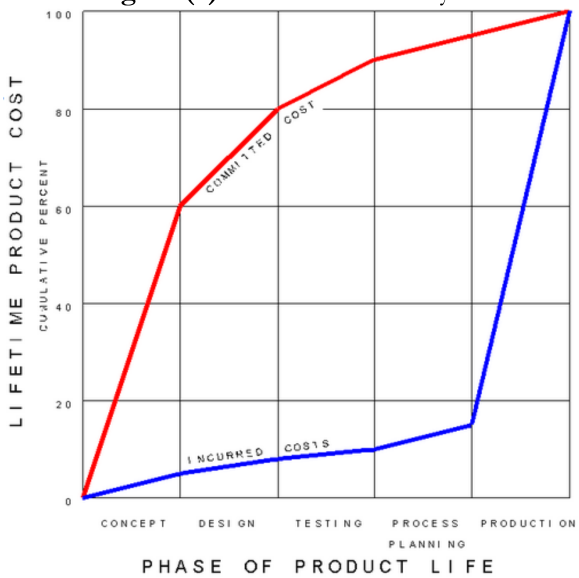
Source: (Adiano & Roth, 1994).

3.1 Design to cost consideration:

Design to Cost is about getting down to the core cost of the product. The goal is to reduce non-core parts of the products for example features that are not considered vital for the company. The aim for the approach is to get the best possible cost level for a product given a defined specification. Things to work on to achieve this are to reduce over-specification and improve production. The approach can be performed both for existing products and for new products (Damlin & sundquist, 2013).

By the time a product has been designed, only 8% of the total product budget has been spent. By that time, the design has determined 80% of the cost of the product. The stage of designing the product for manufacturability is one of the most important phases in the whole value chain of the product (Anderson, 2013).

Figure (5): Product cost life cycle.



Source: (Zain, 2016)

The conclusion of this figure is that the concept and design phases of the product determine 80% of the total costs while the actual costs of these stages wouldn't exceed 10% of the total costs of the product.

To apply the design to cost concept, the management needs first to set both design, performance and cost goals. Then the design team shall design a prototype for the product guided by the goals set by the management. The prototype designed should be compared with the expected design to reach the percentage of completion of the established goals. A final design is to be done after making the edits required to increase the percentage of completion. Finally, the design shall be passed to the manufacturing team in order to implement it (Zain, 2016).

3.2 Achieving cost rationality through the should costs concept

Should Cost focuses on breaking down the cost structure of a supplier before purchasing in order to get the right cost from the start. Should Cost focus also on obtaining knowledge of the actual price of the product before purchasing in order to get a better negotiation position and map the "best-case" cost structure of the component (Damlin and Sundquest, 2013).

As, the price is one of the most important elements in the purchasing decision since increases in material prices cannot always be passed on to the customer.

Purchasing price is ultimately the result of environmental factors, both internal and external. Industrial salesmen will attempt to hide their cost structures since it is in their interest that this information remains obscure to the buyer (Weele, 2010).

The Should costs approach would help to get the organization an insight in the cost structure of the suppliers to make the needed acquisitions with the best available price in the first stage of the product's life cycle. Using the Design to cost concept would enable the organization to design a new product that meets customers' needs and within the targeted costs. Also using the benchmarking technique that helps the organization to know the best usage of the available resources to avoid wasting the resources (Zain, 2016).

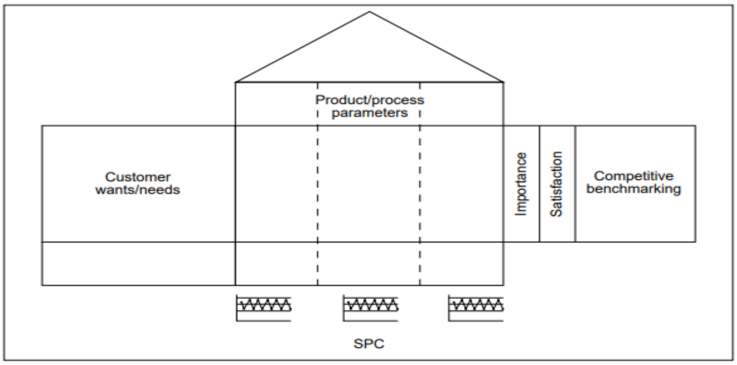
3.3 The Mechanism of Dynamic Quality function deployment:

The Mechanism of Dynamic Quality function deployment can be summarized as follows (Adiano & Roth, 1994):

Dynamic QFD incorporates traditional QFD logic as originally intended for apply, significant modifications are necessary to exploit its potential as a decision support system. Specially, the underlying logic of dynamic QFD captures the advantages of real-time, customer feedback response, and statistical process control., It monitors control limits and process capabilities for continuous improvement to guide manufacturing and supplier activities. The dynamic QFD model gives manufacturing a new competitive weapon due to its performance can be tied directly to customer satisfaction data through feedback loops.

The house of quality structure is the primary inter-functional planning and communications model in dynamic QFD. To differentiate dynamic QFD from the traditional QFD, the basic structure is newly defined as the house of the customer. The first house of the customer maps manufacturing product-process parameters to customer needs. The following figure 6 shows House of the Customer.

Figure (6): House of the Customer.



Source: (Adiano & Roth, 1994).

Following matrices can be used to cascade manufacturing product-process parameters to other value chain partners such as materials suppliers. Tying together these three value chain partners (customers, manufacturer, and suppliers) qualifies this model as a development model, for example, decision-support system for continuous improvement.

Dynamic QFD transmit the customer voice back through the value chain elements over the product life cycle in the following manner. After establishing the initial design using up to four houses, product-process parameter data is collapsed into one house. This may be completion by additional matrices for up to three value chain elements.

Manufacturing process parameters replace the engineering properties definition in the original house of quality. In order to implement a real-time response environment, ongoing customer feedback is chosen to drive real-time improvements in the manufacturing and supplier areas, thus maximizing the potential to produce consistently, quality product. Notably, like traditional QFD, needs and priorities are defined in the customers' natural language, and not in technical terms.

One of the initial challenges in applying the dynamic QFD is to define who are the process customers. In manufacturing, downstream process centers are often referred to as "internal customers" (Gopalakrishnan, 1992). The end-users, or external customers, are ultimately responsible for the firm's survival and profitability and, therefore, are prioritized. Thus, the external customers' requirements and desires are collected first along with survey assessments of the relative importance of each and their current levels of consent with each.

External customer information is systematically entered into the house. Griffin and Hauser (Thommie &Timothy, 2014) provide an important critical review of how to identify the customer voice. They empirically examine the stated objective of QFD, customer satisfaction.

Customer survey outcomes are reviewed with the team of key process owners and stakeholders. The team identify the product-process parameters that match valid customer desires and requirements. The product-process parameters are entered into the house.

Ultimately, the mechanism of defining the quality plan, sales points, product/parameter relationships, correlations, and target values are completed and put into the house. Once completed, the decision support system activates the dynamic house of the customer. The product is shipped along with the customer satisfaction survey; and the house awaits the customer feedback.

When the survey findings are returned by the customers, they are fed back into the system and updates to the house are made. The system automatically flags any significant upward or downward trends in customer satisfaction or relative importance using statistical process control charts. Decision support software inspects process parameters for possible causes of dissatisfaction and provides a prioritized list of process and product parameters in need of improvement based upon customer observations. From this list recommendations can be made to the various value chain process owners. In this way, dynamic QFD provides strategic and proactive support to operational effectiveness across the manufacturing limitations. In dynamic QFD, the manufacturing processes become more market driven, giving support for the smoothly organization determined by (Yih &Chun-Hsien, 2010).

4. The Adoption of Artificial Intelligence Forecasting Techniques:

Cost prediction is a vital process for every business in that it is a predecessor for budget prices and resource allocation in a project life cycle. Actually, it is hard to obtain input data for cost estimation process, while the scope of work is barely known in that it might lead to poor and rough estimates. The more, the project scope is known there are more chances to generate estimates that are more accurate in that more specifications of the project are defined. However, it should be taken into account that, on the other hand, by the progressive elaboration, the process of cost control becomes more difficult if the project is based on inaccurate cost estimates (Hashemi, et al., 2020).

Either overestimating or underestimating the cost of the projects will lead to future deviations in budget vs. realized cost. Hence, the methods used in this realm, their respective accuracy, and even their gaps have shown growing interest. Methods with more consistent results can facilitate and smooth the path for cost estimators provided that their related gaps can be investigated and overcome in order to acquire better results. In conventional methods, by knowing work packages and their prices and how they are distributed along the project lifetime; the total project cost can be estimated. Which this will be an input for project resource allocation and further budget calculations. The conventional methods have shown that they are not merely enough. Thereby the lack of a systematic approach in order to reduce the error of the estimation process has entailed in studies that most of all have tried to take advantage of mathematical models, machine learning techniques, and so on to overcome inaccurate or may even erroneous predictions (Hashemi, et al., 2020).

Product cost estimation is a topic of great importance for all manufacturing and producing companies (Chou and Tsai, 2012; Loyer et al., 2016). During product development, overestimation of cost could mistakenly discard profitable products, while underestimation of cost creates the risk of producing at loss. Niazi et al.'s (2006) framework of product cost estimation divides methods into quantitative and qualitative techniques. Quantitative techniques make use of the knowledge about design, materials, and processes of a product and can be divided into parametric and analytical techniques. Parametric techniques derive an equation for costs, using relevant features as input variables. Analytical techniques consider the product as the sum of all necessary units and operations (i.e., break-down approach or activity-based costing). Qualitative techniques compare new products to previous ones to find similarities and can be divided into intuitive and analogical techniques. Intuitive techniques are based on expert experience where the knowledge is usually stored in sets of rules, decision trees, or case-databases. Analogical techniques use historical cost data to train statistical and machine learning models (Hammann, 2024).

Forecasting the costs and the demand together is a very important pillar to a better cost management system. During product development, overestimation of cost could mistakenly discard profitable products, while underestimation of cost creates the risk of producing at loss (Hamman, 2024).

One of the main pillars of cost management and rationalization is the ability to estimate the costs and anticipate the cost flows and costing curriculum. The Forecasted cost data are as good as the inputs of cost data entering the forecasting system. Also, the forecasting techniques are very much affecting the quality of the forecasting process and here comes the Artificial Intelligence Forecasting Techniques role in supporting and developing the forecasting process.

4.1 Neural Network

In cost estimation scope, many models and techniques are used, out of which Artificial Neural Networks (ANNs), hybrid models of ANN with secondary artificial intelligence or meta-heuristic methods, Radial Basis

Function Neural Network (RBFNN); Case-Based Reasoning (CBR), Regression Analysis (RA), Particle Swarm Optimization (PSO), Decision Tree (DT), and Expert Systems are investigated here (Hashemi et.al, 2020).

Artificial neural networks are one of the many algorithms, which are modelling biological learning processes through computers. They are classified under a major categorized named machine learning. In fact, machine learning is the process of programming the computers to improve and optimize a performance based on a past available data or knowledge (Alpaydin, 2014).

The first mathematical model of an artificial neural network model was formulated by McCulloch and Pitts in 1943 (Graupe, 2013). Artificial neural networks known as neural networks are analogy-based, non-parametric information processing systems that have inspired their jobs and structure from the brain's biological neural networks (Anderson & McNeill, 1992).

The greatest challenging problems, which neural networks are used for, are pattern recognition, clustering/classification, and prediction/forecasting. In forecasting problems, neural networks are trained based upon past data and depending upon their generalization ability; they can provide forecasting for novel cases (Hashemi et.al, 2020).

Neural networks have various advantages, including their ability to conduct predictions with less required developed statistical trainings, ability to detect intricate nonlinear relationships between variables, ability to discover all possible interrelations between variables, and the capacity to be developed through the use of numerous training algorithms (Hashemi et.al, 2020). However, like any other subject, there remain some deficiencies, including their "black box" mechanism leading to discouragement in finding the origin of the results, their difficult applicability to some difficulties, their need for high computational resources, and their vulnerability in overfitting and experimental construction, which are highly in need of resolving many matters such as their topology and other methodological matters (Tu, 1996).

On the other hand, ANN is extremely data driven and will be reflected low prediction performance, while being fed with a small number of data, leading to over specification, which means that they can operate well with the available data, but are incapable of predicting novel cases (Bjornson & Barney, 1999) .The application of heuristic rules such as preventing the model from being further trained, while there seems to be no more improvement in the network MSE and also using fewer numbers of nodes in hidden layers can reduce this possibility.

Despite the black box mechanism of neural networks, they have been widely used in prediction issues demonstrating reasonable results as scrutinized in the literature. Developing hybrid model of back propagation neural networks and genetic algorithm will lead to more accurate predictions and prevent the model from providing erroneous performance hence can navigate the encapsulated shortcomings (Bai, 2014).

The use of hybrid models of ANN with secondary artificial intelligence or meta-heuristic techniques such as genetic algorithms, bee colony algorithm, and artificial immune systems have been proposed in numerous articles in order to cover the defects of ANNs and thus enable them to be applied in various problems (Tkáč &Verner, 2016)

Genetic Algorithm (GA), one of these meta-heuristic methods and a family of evolutionary computation models, was first invented by John Holland in 1960s (Mitchell,1998).

Since the improvement problems are occurring in dynamic settings, they require a kind of feedback from the environment, which the problem is taking place regarding the success or even failure of the current applied strategy, that will use the earned knowledge in order to evolve the applied strategies and recombine the best pieces of competing strategies to reproduce much more suitability individuals.

4.2 Machine-learning

Machine learning establishes algorithms that enable computers to learn by finding statistical regularities and patterns in data (Oladipupo, 2010). Machine learning might be important success factors for the cost estimation task during product development, as it does not require pre-defined equations (parametric techniques), detailed descriptions of products and activities (analytical techniques) or expert experience (intuitive techniques).

Machine learning technology offer significant potential benefits for managing costs and economic decision-making in manufacturing companies (Fosso

Wamba et al., 2015; Loyer et al., 2016). While the literature offers many theoretical approaches, frameworks, or conceptual applications of big data and machine learning (Rikhardsson and Yigitbasioglu, 2018; Saggi and Jain, 2018), few empirical studies report actual implementation experiences and realized benefits, and these typically do not focus on cost estimation or cost management (Fosso Wamba et al., 2015; Tan et al., 2015). Cost estimation is important for companies (Ben-Arieh, 2000), especially during product development (Cavalieri et al., 2004). Empirical cost estimation studies mostly focus on the comparison of statistical models according to their predictive performance based on archival data. However, little is known about the actual utilization of these models in practice. So, it is important to better understand how the potential of and machine learning can be realized in cost estimation.

Models based on ML and AI are increasingly being used in a various of applications, including prediction and forecasting.

AI models offer a more sophisticated approach considering different factors. Studies have indicated that ML and AI models can outperform rule-based methods in several ways, including accuracy, speed, and scalability (Ba and Huynh, 2018; Jullum et al., 2020; Singh and Best, 2019). Models based on ML and AI are said to have greater predictive accuracy than the traditional rule-based approach to detection (Chen et al., 2018; Jullum et al., 2020).

Other studies indicated that ML and AI models could deal more quantities of data than traditional rule-based systems and could do so in a fraction of the time (Lokanan, 2019; Salehi et al., 2017; Sarker, 2022).

Machine-learning algorithms are repeatable and, typically, high resolution. Repeatable models allow the modeler to easily refreshed the model once data is updated, e.g. when a larger/newer dataset is available (Mahpour, 2023). On the other hand, statistical models are mostly used when interpretable models are needed. Interpretable models afford the correlations and relationships between features, rather than repeatable and high-accuracy estimations. Also, they are normally less accurate than machine-learning models (Khalil et al.,2022) (Mahpour & El-Diraby, 2022)

ML algorithms are popular and required because they can change as they read new data or forms (Kansal, 2021; Lokanan and Sharma, 2022; Zhang and Trubey, 2019).

Machine Learning (ML) techniques: They include at least one modeling method, taking a number of project advantages and producing a cost prediction, making no or minimal assumptions about the form of the relation under study.

Thus, they can provide higher approximation capabilities to solve complex problems. Representative ML techniques include artificial neural networks (ANN), case-based reasoning (CBR) (also referred to as analogy-based estimation or estimation by analogy), and classification and regression trees (CART) (Huang et. al, 2016).

When targeting estimation accuracy, considerable effort has been devoted to optimize ML techniques. For the empirical validations, ML algorithms are routinely tested on the SCE datasets. Data preprocessing (DP) is an essential phase of the ML application, which has been reported to have significant impacts onto the performances of ML techniques (Huang et. al, 2016).

According to Loyer et al. (2016), intelligent cost estimation methods including machine learning (ML) technique have the ability to significantly reduce the effort of traditional bottom-up cost calculation. This is due to the fact that less detailed information about the product and its production process is essential (Loyer et al., 2016).

Machine learning and big data techniques offer significant potential benefits for rationalizing costs and economic decision-making in manufacturing companies (Chou et al., 2010; Fosso Wamba et al., 2015; Loyer et al., 2016).

5. The Empirical Analysis:

The empirical analysis starts with data collection procedures which is represented in the questionnaire followed by Statistical analysis and its techniques to test the research hypothesis. This is followed by applying both descriptive statistics such as frequencies, percentages, means, standard deviation, and coefficient of variation, and analytical statistical techniques to analyze research data such as the one sample t-test to validate the research hypothesis. (EFA) was used to explain the relationships among several difficult correlated variables for each research construct to produce a few conceptually meaningful, relatively independent factors to get the percent of variance accounted for by each specific factor or component, relative to the total variance in all the variables. Finally, Alpha Cronbach coefficient for reliability and intrinsic face validity model of internal consistency, based on the average inter-item correlation, for all independent and dependent Variables. Results are reviewed and the chapter is concluded with a summary.

5.1 Procedures and Statistical Analysis Techniques:

The following statistical Procedures are used in this research:

(A)- Data entry:

The researcher has checked all items of survey to ensure the validity and excludes the items not sufficiently answered, then codes all variables according to Statistical Package for Social Science (SPSS).

In the reported analysis, the data comprises the following:

(1) Independent Variables:

The independent variables will be the following:

1. Accurate demand and cost forecasting tool.
2. Dynamic quality function deployment model.

(2) Moderating Variable:

1. Dynamic Business Environment.

(3) Dependent Variable:

1. Cost rationalization of the short life cycle products.

(B)-0 The Population:

The population consists of both; the professional accountants who works in the field of the cost accounting and managerial accounting in the short life-cycle products' industrial organizations -Technology and Fashion- represented by (Samsung, Crystal, Mobaco Cotton, Swiss clothing, LG, Camget, BTM, El Masaeed, EL Shafaee, TIE, Nile, Cairo Cotton, Lotus, and National) and also the academics who are staff members in faculties of commerce or business administration in the Egyptian universities (Nahda university, Helwan university, Beni-Suef university, Cairo university, Sadat academy, 6th October university, MUST university).

(C)- The sample size:

The sample size formulas and procedures used for categorical data are very similar, but some variations do exist. Assume a researcher has set the alpha level a priori at 0.05, plans to use a proportional variable, has set the level of acceptable error at 5%, and has estimated the standard deviation of the scale as 0.5. Cochran's sample size formula for categorical data and an example of its use is presented here along with explanations as to how these decisions were made.

$$n = \left(\frac{(z_{\alpha/2})^2 (p)(1-p)}{(d)^2} \right)$$

Where that:

$Z_{\alpha/2}$ = value for selected alpha level of .025 in each tail = 1.96.

(p) (q) = estimate of variance = 0.25.

d = acceptable margin of error for proportion being estimated = 0.05.

$$n = \left(\frac{(1.96)^2 (0.5)(0.5)}{(0.05)^2} \right) = 384$$

Where n = required return sample size according to Cochran's formula= 384

Table (1): The sample Size respondents for academics and professionals

No. of sent questioners	No. of received questioners	% respondents	% non-respondents
384	302	78.6	21.4

5.2 Descriptive statistics for demographic variables:

The researcher has carried out descriptive statistics, including frequencies, percentages, means, standard deviation, and coefficient of variation, for all characteristics of the sample, independent and dependent variables. These descriptive statistics are based on ordinal likert scale.

It can be concluded from table 2 that the professional Cost accountants in the manufacturing organizations represents 62.6% of the sample while the academics represent 37.4% of the sample.

Table (2): Descriptive statistics for the field of experience:

Description	Frequency	Percentage
Academic	113	37.4 %
Professional	189	62.6 %
Total	**302**	**100%**

Table (3): Descriptive statistics for the Period of experience:

Description	Frequency	Percentage
Less than 5 years	53	17.5%
Between 5 years and 10 years	119	39.4%
More than 10 years	130	43.0%
Total	**302**	**100%**

It can be concluded from table 3 that 17.5% of the population participated in the questionnaire have an experience period less than 5 years, 39.4% of the population participated in the questionnaire have an experience period between 5 years and 10 years, and 43.0% of the population participated in the questionnaire have an experience more than 10 years.

5.3 Reliability and intrinsic validity for research variables:

Table (4): Reliability and intrinsic validity for research variables

No.	Dimension	Reliability Coefficient	Intrinsic Validity
1	The Special Nature of short life-cycle products.	0.858	0.9262
2	The demand of the short life-cycle products under dynamic quality function deployment and AI tools.	0.801	0.8949
3	The cost rationalization through DQFD and AI tools.	0.848	0.9208
Total		**0.937**	**0.9679**

According to table 4 it was found thaishe reliability coefficient and intrinsic validity for the research dimensions are (0.937), (0.9679) respectively; highly internal consistency based on the average inter-item correlation. The most three dimensions with highly reliability coefficients are: The Special nature of short life-cycle products, The demand of the short life cycle products under dynamic quality deployment, and the cost and demand prediction through AI tools, with reliability coefficient (0.858), (0.801), (0.848) respectively.

5.4 Descriptive statistics for the research variables:

Table (5): Descriptive statistics for the existence of the short life-cycle products

No.	Statements	MEAN	SD	CV	Rank
1	The rapid growth in the industry led to shortening the life cycle of the products.	4.69	0.555	11.83	1
2	The products that have a life cycle period between 3 months and 1 year are considered a short life-cycle products.	4.56	0.633	13.88	3
3	There is a lack of the historical sales data regarding the short life-cycle products.	3.90	0.999	25.62	10
4	It's difficult to forecast the future demand of the short life-cycle products due to the lack of historical sales data.	3.91	1.056	27.01	11
5	The difficulty in forecasting the future sales could result a mismatching between the supply and the demand.	4.02	0.917	22.81	8
6	The mismatching between the supply and the demand would result an extra cost to the organization.	4.36	0.565	12.96	2
7	The inventory of the short life-cycle products has a high speed deterioration feature.	4.00	1.016	25.40	9

No.	Statements	MEAN	SD	CV	Rank
8	The lead time of the short life-cycle products is longer than other types of products.	4.11	0.907	22.07	7
9	The demand of the short life-cycle products is fluctuating.	4.26	0.643	15.09	4
10	The prices of the parts to be used in manufacturing the short life-cycle products are extremely volatile.	4.13	0.772	18.69	6
11	The new features or attributes imposed in the new remanufactured products represents the greatest portion of the costs.	4.29	0.744	17.34	5
Total		**4.4917**	**0.49155**	**10.94**	**--**

According to Descriptive statistics in table 5, it can be concluded that:

- The most five homogeneous variables are: The rapid growth in the industry led to shortening the life cycle of the products, the mismatching between the supply and the demand would result an extra cost to the organization, the products that have a life cycle period between 3 months and 1 year are considered a short life-cycle product, the demand of the short life-cycle products is fluctuating, and the new features or attributes imposed in the new remanufactured products represents the greatest portion of the costs. With coefficient of variation (11.83), (12.96), (13.88), (15.09), and (17.34) respectively.
- On the other hand, the most five heterogeneous variables are: It's difficult to forecast the future demand of the short life-cycle products due to the lack of historical sales data, there is a lack of the historical sales data regarding the short life-cycle products, the inventory of the short life-cycle products has a high speed deterioration feature, the difficulty in forecasting the future sales could result a mismatching between the supply and the demand, and The lead time of the short life-cycle products is longer than other types of products. With coefficient of variation (27.01), (25.62), (25.40), (22.81), and (22.07) respectively.
- While the value of total weighted mean for the existence of the sort life-cycle products is (4.4917), with coefficient of variation (10.94), therefore we have a totally agree direction to the existence of the short life-cycle products dimension.

The demand of the short life cycle products under dynamic quality function deployment and AI tools.

Table (6): Descriptive statistics for the demand of the short life-cycle products under dynamic quality function deployment and AI tools:

No.	Statements	MEAN	SD	CV	Rank
1	The demand forecasting affects the cost rationalization process.	4.44	0.589	13.27	1
2	The traditional demand forecasting models are not suitable for the short life-cycle products.	3.77	1.065	28.25	7
3	The accuracy of the forecasting process depends upon the volume of the available data.	4.38	0.602	13.74	3
4	Defining customer needs and attribute analysis before designing the product enhances demand on SLCPs	4.15	0.751	18.10	4
5	The seasonality factors affect the demand of the short life-cycle products.	4.16	0.884	21.25	6
6	Using the dynamic quality function deployment can help to minimize the redesigning times.	3.81	1.274	33.44	9
7	Reducing redesigning times will help to reduce the costs of R&D Stage.	4.22	0.765	18.13	5
8	Involving the customer in the R&D stage have a great impact on the demand size.	4.52	0.603	13.34	2
9	The quality of the products is considered to be the main factor influencing the demand quantity.	3.80	1.226	32.26	8
Total		**4.1209**	**0.75886**	**18.41**	**--**

According to Descriptive statistics in table 6, it can be concluded that:

- The most four homogeneous variables are: The demand forecasting affects the cost rationalization process, Involving the customer in the R&D stage have a great impact on the demand size, the accuracy of the forecasting process depends upon the volume of the available data, defining customer needs and attribute analysis before designing the product enhances demand on SLCPs. With coefficient of variation (13.27), (13.34), (13.74), and (18.10) respectively.
- On the other hand, the most four heterogeneous variables are: Using the dynamic quality function deployment can help to minimize the redesigning times, the quality of the products is considered to be the main factor influencing the demand quantity, the traditional demand forecasting models are not suitable for the short life-cycle products, the seasonality factors affect the demand of the short life-cycle products. With coefficient of variation (33.44), (32.26), (28.25), and (21.25) respectively.

- While the value of total weighted mean for The demand of the short life-cycle products under dynamic quality function deployment and AI tools. is (4.1209), with coefficient of variation (18.41), therefore we have an agree direction to The demand of the short life-cycle products under dynamic quality function deployment and AI tools.

The cost and demand prediction through DQFD and AI tools.

Table (7): Descriptive statistics for the cost and demand prediction through DQFD and AI tools:

No.	Statements	MEAN	SD	CV	Rank
1	The main objective of the cost rationalization process is to minimize the costs all over the product's life cycle.	4.55	0.579	12.73	5
2	It's a must to avoid the minimization of employees' benefits in the cost rationalization process.	4.09	0.755	18.46	19
3	The cost rationalization concerns the most with the waste minimization.	4.50	0.709	15.76	17
4	The costs of the research and development stage represents a huge portion of the whole costs of the production.	4.53	0.608	13.42	9
5	Using the "Design to cost" approach would help the organization to minimize the costs related to the research and development stage of the supply chain.	4.36	0.598	13.72	11
6	The Procurement costs are considered as a major cost driver in the life cycle of the product.	4.29	0.555	12.94	7
7	Using the "Should costs" concept shall provide the organization with an insight of the cost structure of the supplier.	4.02	0.845	21.02	20
8	The availability of the data regarding the suppliers' cost structure shall accordingly result a save in the procurement costs.	4.30	0.636	14.79	15
9	Using the machine learning tool provides the organization with an Insight about the best quantity to be produced.	3.88	1.242	32.01	22
10	Knowing the best available usage of the resources shall contribute positively in the cost rationalization process.	4.55	0.561	12.33	4
11	The data gathered using the machine learning tool would help to apply both "Design to cost" and "Should costs".	4.36	0.691	15.85	18

No.	Statements	MEAN	SD	CV	Rank
12	The after sale costs of the short life-cycle products are relatively higher than these costs in other products.	3.71	1.261	33.99	23
13	The quality of the short life cycle products has a major impact upon the after sale costs.	4.52	0.551	12.19	3
14	The use of dynamic quality function deployment can improve the efficiency and effectiveness of the manufacturing of the short life-cycle products.	4.36	0.558	12.80	6
15	Using the dynamic quality function deployment along with the "Design to cost" concept shall help the organization to achieve the optimal product design.	4.35	0.596	13.70	10
16	The huge ability to gather information regarding the seasonality factors using AI could facilitate the demand forecasting process.	4.18	1.138	27.22	21
17	Developing a life cycle curve for the short life-cycle products shall help in minimizing the mismatch between the supply and the demand.	4.49	0.533	11.87	1
18	Not manufacturing of all the quantity that will be supplied in the markets at once but divided into smaller sales periods instead, shall help in minimizing the mismatch between the supply and the demand.	4.42	0.630	14.25	14
19	Using the dynamic quality function deployment shall help the organization to get over the administrative problems which the organization used to suffer from its costs in order to achieve the desired cost rationality.	4.37	0.616	14.10	13
20	Using the dynamic quality function deployment model helps the organization to achieve the lowest defect rate which consequently minimize the costs of the organization to the minimum.	4.36	0.662	15.18	16
21	Using dynamic quality function deployment would help in rationalizing the costs of the manufacturing stage of the supply chain of the short life-cycle products.	4.61	0.615	13.34	8
22	Reducing designing time and redesigning times shall minimize the waste and consequently rationalize the costs.	4.68	0.570	12.18	2

No.	Statements	MEAN	SD	CV	Rank
23	It's a must to determine correctly the needed quantity of production for the season before it starts to avoid keeping inventory.	4.62	0.651	14.09	12
Total		**4.5811**	**0.46026**	**10.05**	**--**

According to Descriptive statistics in table 7, it can be concluded that:

- The most six homogeneous variables are: developing a life cycle curve for the short life-cycle products shall help in minimizing the mismatch between the supply and the demand, Reducing designing time and redesigning times shall minimize the waste and consequently rationalize the costs, the quality of the short life cycle products has a major impact upon the after sale costs, knowing the best available usage of the resources shall contribute positively in the cost rationalization process, the main objective of the cost rationalization process is to minimize the costs all over the product's life-cycle, and The use of dynamic quality function deployment can improve the efficiency and effectiveness of the manufacturing of the short life-cycle products. With coefficient of variation (11.87), (12.18), (12.19), (12.33), (12.73) and (12.80) respectively.

- On the other hand, the most six heterogeneous variables are: the after sale costs of the short life-cycle products are relatively higher than these costs in other products, Using the machine learning tool provides the organization with an Insight about the best quantity to be produced, The huge ability to gather information regarding the seasonality factors using AI could facilitate the demand forecasting process, using the "Should costs" concept shall provide the organization with an insight of the cost structure of the supplier, it's a must to avoid the minimization of employees' benefits in the cost rationalization process, The data gathered using the machine learning tool would help to apply both "Design to cost" and "Should costs". With coefficient of variation (33.99), (32.01), (27.22), (21.02), (18.46), and (18.85) respectively.

- While the value of total weighted mean for The cost rationalization through DQFD and AI tools.is (4.5811), with coefficient of variation (10.05), therefore we have a totally agree direction to the cost rationalization through DQFD and AI tools.

5.5 Factor Analysis:

Exploratory factor analysis for research constructs:

The researcher used (EFA) to explain the relationships among several difficult correlated variables for each research construct to produce a few conceptually meaningful, relatively independent factors to get the percent of variance accounted for by each specific factor or component, relative to the total variance in all the variables as the following:

The short life cycle products

Table (8): KMO and Bartlett's Test of Sphericity:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.809
Bartlett's Test of Sphericity	Approx. Chi-Square	1307.791
	df	55
	Sig.	.000

- Kaiser-Meyer-Olkin Measure of Sampling Adequacy, KMO, for sampling adequacy, should be greater than 0.50 or equal.
- Bartlett's test of sphericity indicates whether your correlation matrix is an identity matrix, which would indicate that your variables are unrelated. The significance level gives the result of the test. Very small values (less than 0.05) indicate that there are probably significant relationships among variables.

Table (9): Rotation Sums of Squared Loadings

No	Factors	Eigen values λ	% of Variance	Cumulative %
1	1st factor	4.321	39.283	39.283
2	2nd factor	1.523	13.848	53.131

According to Descriptive statistics in table 9, it can be concluded that:

- Eigen values represent the amount of variance accounted for by a factor by sum of squared loadings for a factor at the optimum value greater than one.
- The "% of Variance" gives the percent of variance accounted for by each specific factor or component, relative to the total variance in all the

variables while the optimum value for Cumulative Rotation Sums of Squared Loadings (0.50) at least.

- Patients' Rights Charter constructs represent (53%) from the Total Variance Explained.

Table (10): Rotated Component Matrix

No.	1st factor		2nd factor	
	Variables	**factor loadings**	**Variables**	**factor loadings**
1	There is a lack of the historical sales data regarding the short life-cycle products.	0.821	The rapid growth in the industry led to shortening the life cycle of the products.	0.800
2	The inventory of the short life-cycle products has a high speed deterioration feature.	0.819	The products that have a life cycle period between 3 months and 1 year are considered a short life-cycle products.	0.784
3	It's difficult to forecast the future demand of the short life-cycle products due to the lack of historical sales data.	0.808		
4	The difficulty in forecasting the future sales could result a mismatching between the supply and the demand.	0.792		
5	The demand of the short life-cycle products is fluctuating.	0.689		
6	The prices of the parts to be used in manufacturing the short life-cycle products are extremely volatile.	0.623		
7	The lead time of the short life-cycle products is longer than other types of products.	0.584		
8	The mismatching between the supply and the demand would result an extra cost to the organization.	0.560		
9	The new features or attributes imposed in the new remanufactured products represents the greatest portion of the costs.	0.406		

According to Descriptive statistics in table 10, it can be concluded that:

- This table (called the Pattern Matrix for varimax rotations) reports the factor loadings for each variable on the components or factors after rotation
- Each number represents the partial correlation between the item and the rotated factor at minimum correlation coefficient from (0.30) to (0.50).

The demand of the short life-cycle products

Table (11): KMO and Bartlett's Test of Sphericity:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.737
Bartlett's Test of Sphericity	Approx. Chi-Square	1040.367
	df	36
	Sig.	.000

- Kaiser-Meyer-Olkin Measure of Sampling Adequacy, KMO, for sampling adequacy, should be greater than 0.50 or equal.
- Bartlett's test of sphericity indicates whether your correlation matrix is an identity matrix, which would indicate that your variables are unrelated. The significance level gives the result of the test. Very small values (less than 0.05) indicate that there are probably significant relationships among variables.

According to Descriptive statistics in table 12, it can be concluded that:

- Eigen values represent the amount of variance accounted for by a factor by sum of squared loadings for a factor at the optimum value greater than one.
- The "% of Variance" gives the percent of variance accounted for by each specific factor or component, relative to the total variance in all the variables while the optimum value for Cumulative Rotation Sums of Squared Loadings (0.50) at least.
- Patients' Rights Charter constructs represent (58%) from the Total Variance Explained.

Table (12): Rotation Sums of Squared Loadings

No	Factors	Eigen values λ	% of Variance	Cumulative %
1	1st factor	2.697	29.965	29.965
2	2nd factor	2.517	27.970	57.935

Table (13): Rotated Component Matrix

No.	1st factor		2nd factor	
	Variables	factor loadings	Variables	factor loadings
1	The seasonality factors affect the demand of the short life-cycle products.	0.776	The quality of the products is considered to be the main factor influencing the demand quantity.	0.875
2	The demand forecasting affects the cost rationalization process.	0.670	The traditional demand forecasting models are not suitable for the short life-cycle products.	0.864
3	Reducing redesigning times will help to reduce the costs of R&D Stage.	0.666	Defining customer needs and attribute analysis before designing the product enhances demand on SLCPs	0.783
4	Involving the customer in the R&D stage have a great impact on the demand size.	0.620		
5	Using the dynamic quality function deployment can help to minimize the redesigning times.	0.611		
6	The accuracy of the forecasting process depends upon the volume of the available data.			

According to Descriptive statistics in table 13, it can be concluded that:

- This table (called the Pattern Matrix for varimax rotations) reports the factor loadings for each variable on the components or factors after rotation
- Each number represents the partial correlation between the item and the rotated factor at minimum correlation coefficient from (0.30) to (0.50).

The cost rationalization process:

Table (14): KMO and Bartlett's Test of Sphericity:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.790
Bartlett's Test of Sphericity	Approx. Chi-Square	2399.966
	df	171
	Sig.	.000

- Kaiser-Meyer-Olkin Measure of Sampling Adequacy, KMO, for sampling adequacy, should be greater than 0.50 or equal.
- Bartlett's test of sphericity indicates whether your correlation matrix is an identity matrix, which would indicate that your variables are unrelated. The significance level gives the result of the test. Very small values (less than 0.05) indicate that there are probably significant relationships among variables.

Table (15): Rotation Sums of Squared Loadings

No	Factors	Eigen values λ	% of Variance	Cumulative %
1	1st factor	4.837	25.458	25.458
2	2nd factor	3.279	17.259	42.717

According to Descriptive statistics in table 15, it can be concluded that:

- Eigen values represent the amount of variance accounted for by a factor by sum of squared loadings for a factor at the optimum value greater than one.
- The "% of Variance" gives the percent of variance accounted for by each specific factor or component, relative to the total variance in all the variables while the optimum value for Cumulative Rotation Sums of Squared Loadings (0.50) at least.
- Patients' Rights Charter constructs represent (43%) from the Total Variance Explained.

Table (16): Rotated Component Matrix

No.	1st factor		2nd factor	
	Variables	**factor loadings**	**Variables**	**factor loadings**
1	Using the machine learning tool provides the organization with an Insight about the best quantity to be produced.	0.888	Using dynamic quality function deployment would help in rationalizing the costs of the manufacturing stage of the supply chain of the short life-cycle products.	0682
2	The after sale costs of the short life-cycle products are relatively higher than these costs in other products.	0.883	The use of dynamic quality function deployment can improve the efficiency and effectiveness of the manufacturing of the short life-cycle products.	0.639
3	Using the "Should costs" concept shall provide the organization with an insight of the cost structure of the supplier.	0.769	The costs of the research and development stage represents a huge portion of the whole costs of the production.	0.613
4	The huge ability to gather information regarding the seasonality factors using AI could facilitate the demand forecasting process.	0.766	Using the dynamic quality function deployment along with the "Design to cost" concept shall help the organization to achieve the optimal product design.	0.595
5	The data gathered using the machine learning tool would help to apply both "Design to cost" and "Should costs".	0.676	The cost rationalization concerns the most with the waste minimization.	0.547
6	It's a must to avoid the minimization of employees' benefits in the cost rationalization process.	0.646	Using the dynamic quality function deployment shall help the organization to get over the administrative problems which the organization used to suffer from its costs in order to achieve the desired cost rationality.	0.546
7	Developing a life cycle curve for the short life-cycle products shall help in minimizing the	0.536	Using the "Design to cost" approach would help the organization to minimize the costs related to the	0.526

No.	1st factor		2nd factor	
	Variables	factor loadings	Variables	factor loadings
	mismatch between the supply and the demand.		research and development stage of the supply chain.	
8	The Procurement costs are considered as a major cost driver in the life cycle of the product.	0.482	Using the dynamic quality function deployment model helps the organization to achieve the lowest defect rate which consequently minimize the costs of the organization to the minimum.	0.494
9	The availability of the data regarding the suppliers' cost structure shall accordingly result a save in the procurement costs.	0.480	It's a must to determine correctly the needed quantity of production for the season before it starts to avoid keeping inventory.	0.447
10	not manufacturing of all the quantity that will be supplied in the markets at once but divided into smaller sales periods instead, shall help in minimizing the mismatch between the supply and the demand.	0.467		

According to Descriptive statistics in table 16, it can be concluded that:

- This table (called the Pattern Matrix for varimax rotations) reports the factor loadings for each variable on the components or factors after rotation
- Each number represents the partial correlation between the item and the rotated factor at minimum correlation coefficient from (0.30) to (0.50).

5.6 Testing the hypothesis:

There are three different hypotheses in this research:

H1: There is a statistical relationship between the adoption of the dynamic quality function deployment model and demand enhancement.

H2: There is a statistical relationship between demand enhancement and cost rationalization.

H3: There is a statistical relationship between the accuracy of demand forecasting and cost rationalization.

The first research hypothesis: There is a statistical relationship between the adoption of the dynamic quality function deployment model and demand enhancement.

The statistical tool is one sample T-test to measure the use of dynamic quality function deployment, will simplify the major task of enhancing the demand for costs of the short life-life cycle products.

Table (17): T-test to measure the significant differences between sample's mean and population's parameter (μ = 3.4) for hypothesis (H2)

No.	Dimension	MEAN	SE	T-Test	Significant level
1	The demand forecasting affects the cost rationalization process.	4.44	0.034	30.776	0.001***
2	The traditional demand forecasting models are not suitable for the short life-cycle products.	3.77	0.061	6.064	0.001***
3	The accuracy of the forecasting process depends upon the volume of the available data.	4.38	0.035	28.297	0.001***
4	Defining customer needs and attribute analysis before designing the product enhances demand on SLCPs	4.15	0.043	17.264	0.001***
5	The seasonality factors affects the demand of the short life-cycle products.	4.16	0.051	14.990	0.001***
6	Using the dynamic quality function deployment can help to minimize the redesigning times.	3.81	0.073	5.612	0.001***
7	Reducing redesigning times will help to reduce the costs of R&D Stage.	4.22	0.044	18.671	0.001***
8	Involving the customer in the R&D stage have a great impact on the demand size.	4.52	0.035	32.183	0.001***
9	The quality of the products is considered to be the main factor influencing the demand quantity.	3.80	0.071	5.640	0.001***
Total		**4.1209**	**0.04367**	**16.508**	

*** Parameter is significant at the (0.001***) level.

According to T-test in table 17, it can be concluded that:

There are significant differences between sample's mean and population's parameter (**μ** = 3.4), at significant level less than (0.001***) in terms of all variables and total construct regarding an accurate demand forecasting tool, will simplify the major task of enhancing the demand of the short life-life cycle products. Therefore, we reject null hypothesis that (**μ** = 3.4) according to five Likert scale, and we accept alternative hypothesis that (**μ** > 3.4). This validates the hypothesis which said that "There is a statistical relationship between the adoption of the dynamic quality function deployment model and demand enhancement."

The Second research hypothesis: There is a statistical relationship between demand enhancement and cost rationalization.

The statistical tool is one sample T-test to measure demand enhancement effect, on simplifying the major objective of rationalizing the costs for the short life-life cycle products.

Table (18): T-test to measure the significant differences between sample's mean and population's parameter (μ = 3.4)

No.	Dimension	MEAN	SE	T-Test	Significant level
1	The rapid growth in the industry led to shortening the life cycle of the products.	4.69	0.032	40.347	0.001***
2	The products that have a life cycle period between 3 months and 1 year are considered a short life-cycle products.	4.56	0.036	31.753	0.001***
3	There is a lack of the historical sales data regarding the short life-cycle products.	3.90	0.057	8.770	0.001***
4	It's difficult to forecast the future demand of the short life-cycle products due to the lack of historical sales data.	3.91	0.061	8.456	0.001***
5	The difficulty in forecasting the future sales could result a mismatching between the supply and the demand.	4.02	0.053	11.689	0.001***
6	The mismatching between the supply and the demand would result an extra costs to the organization.	4.36	0.032	29.681	0.001***

No.	Dimension	MEAN	SE	T-Test	Significant level
7	The inventory of the short life-cycle products has a high speed deterioration feature.	4.00	0.058	10.315	0.001***
8	The lead time of the short life-cycle products is longer than other types of products.	4.11	0.052	13.596	0.001***
9	The demand of the short life-cycle products is fluctuating.	4.26	0.037	23.297	0.001***
10	The prices of the parts to be used in manufacturing the short life-cycle products are extremely volatile.	4.13	0.044	16.347	0.001***
11	The new features or attributes imposed in the new remanufactured products represents the greatest portion of the costs.	4.29	0.043	20.888	0.001***
Total		**4.4917**	**0.02829**	**38.596**	

*** Parameter is significant at the (0.001***) level.

According to T-test in table 18 it can be concluded that:

There are significant differences between sample's mean and population's parameter (**μ** = 3.4), at significant level less than (0.001***) in terms of the existence of the short life-cycle products.

The Third research hypothesis: "There is a statistical relationship between the accuracy of demand forecasting and cost rationalization"

The statistical tool is one sample T-test to measure the relationship between the accuracy of demand forecasting and cost rationalization.

Table (19): T-test to measure the significant differences between sample's mean and population's parameter (μ = 3.4) for hypothesis (H1)

No.	Dimension	MEAN	SE	T-Test	Significant level
1	The main objective of the cost rationalization process is to minimize the costs all over the product's life cycle.	4.55	0.033	34.417	0.001***
2	It's a must to avoid the minimization of employees' benefits in the cost rationalization process.	4.09	0.043	15.784	0.001***
3	The cost rationalization concerns the most with the waste minimization.	4.50	0.041	27.026	0.001***

No.	Dimension	MEAN	SE	T-Test	Significant level
4	The costs of the research and development stage represents a huge portion of the whole costs of the production.	4.53	0.035	32.195	0.001***
5	Using the "Design to cost" approach would help the organization to minimize the costs related to the research and development stage of the supply chain.	4.36	0.034	27.922	0.001***
6	The Procurement costs are considered as a major cost driver in the life cycle of the product.	4.29	0.032	28.006	0.001***
7	Using the "Should costs" concept shall provide the organization with an insight of the cost structure of the supplier.	4.02	0.049	12.680	0.001***
8	The availability of the data regarding the suppliers' cost structure shall accordingly result a save in the procurement costs.	4.30	0.037	24.646	0.001***
9	Using the machine learning tool provides the organization with an Insight about the best quantity to be produced.	3.88	0.071	6.680	0.001***
10	Knowing the best available usage of the resources shall contribute positively in the cost rationalization process.	4.55	0.032	35.731	0.001***
11	The data gathered using the machine learning tool would help to apply both "Design to cost" and "Should costs".	4.36	0.040	24.172	0.001***
12	The after sale costs of the short life-cycle products are relatively higher than these costs in other products.	3.71	0.073	4.207	0.001***
13	The quality of the short life cycle products has a major impact upon the after sale costs.	4.52	0.032	35.320	0.001***
14	The use of dynamic quality function deployment can improve the efficiency and effectiveness of the manufacturing of the short life-cycle products.	4.36	0.032	29.937	0.001***
15	Using the dynamic quality function deployment along with the "Design	4.35	0.034	27.804	0.001***

No.	Dimension	MEAN	SE	T-Test	Significant level
	to cost" concept shall help the organization to achieve the optimal product design.				
16	The huge ability to gather information regarding the seasonality factors using AI could facilitate the demand forecasting process.	4.18	0.065	11.844	0.001***
17	Developing a life cycle curve for the short life-cycle products shall help in minimizing the mismatch between the supply and the demand.	4.49	0.031	35.446	0.001***
18	Not manufacturing of all the quantity that will be supplied in the markets at once but divided into smaller sales periods instead, shall help in minimizing the mismatch between the supply and the demand.	4.42	0.036	28.064	0.001***
19	Using the dynamic quality function deployment shall help the organization to get over the administrative problems which the organization used to suffer from its costs in order to achieve the desired cost rationality.	4.37	0.035	27.298	0.001***
20	Using the dynamic quality function deployment model helps the organization to achieve the lowest defect rate which consequently minimize the costs of the organization to the minimum.	4.36	0.038	25.310	0.001***
21	Using dynamic quality function deployment would help in rationalizing the costs of the manufacturing stage of the supply chain of the short life-cycle products.	4.61	0.035	34.163	0.001***
22	Reducing designing time and redesigning times shall minimize the waste and consequently rationalize the costs.	4.68	0.033	38.978	0.001***
23	It's a must to determine correctly the needed quantity of production for the season before it starts to avoid keeping inventory.	4.62	0.037	32.473	0.001***
Total		**4.5811**	**0.02648**	**44.596**	

*** Parameter is significant at the (0.001***) level.

According to T-test in table 19, it can be concluded that:

- There are significant differences between sample's mean and population's parameter (**μ** = 3.4), at significant level less than (0.001***) in terms of all variables and total construct regarding the suggested modifications for the cost rationalization approach for the development and remanufacturing of the short-life cycle products will achieve a reasonable save of the cost. Therefore, we reject null hypothesis that (**μ** = 3.4) according to five Likert scale, and we accept alternative hypothesis that (**μ** > 3.4). This validates the hypothesis which said that "There is a positive relationship between the accuracy of demand forecasting and cost rationalization.".

6. Final remarks, and Recommendations:

It was found that, the traditional cost rationalization attempts are no longer appropriate in a fast evolving business environment that introduces new products regularly.

It was also found that there is a huge considerable amount of waste in the short life cycle products industry represented in the stocked undesirable inventory that need either remanufacturing if possible or disposal. This issue is mostly a result of the inefficient production decisions that supply quantities higher than the market ability to absorb.

This mismatch between supply and demand is an inevitable outcome to the inaccurate forecasting models which out of date that is used in the organization. Artificial intelligence provides the solution to that problem through machine-learning forecasting tools that is able to collect data and self-develop the forecasting process to provide more reliable information about demand.

Rationalizing the production decisions will eventually rationalize the costs of the short life cycle products throughout the value chain starting from R&D and designing the product's prototype and until the actual delivery of the product to the end customer.

It is recommended for any organization working in the field of short life cycle products to adopt a machine-learning forecasting tool in order to be able to anticipate both costs and demand of these products and eventually to be able to achieve cost rationality and enhance profitability.

As the rationality is not only about anticipating the level if demand but also it is about affecting the demand to make sure there is no mismatching between the supply and demand and also to make sure to maximize its profitability from a particular short life cycle product, it is recommended to use the dynamic quality function deployment model that enables the organization to have an accurate insight to the consumer needs.

It's also recommended to adopt the design to cost and should costs techniques of the dynamic quality function deployment to be able to design, manufacture, and deliver a short life cycle product at the lowest possible costs.

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