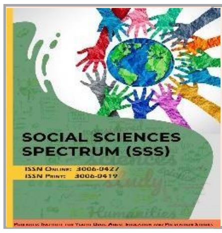

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A Systematic Framework for Integrating Digital Twin Technology and Deep Transfer Learning to Enhance CRM Performance in Pakistan's Textile Industry

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1. Abstract

The numerous stages of manufacturing must be coordinated, information must be freely exchanged, and real-time data feedback must be employed in order to meet Pakistan's enormous demand for mass-produced yarn and overcome these issues. In response this paper proposes a framework built around Model-Based Systems Engineering (MBSE). Low rejection rates and good quality products are critical for the companies to stay competitive, not just locally but internationally as well. Therefore, the shift from traditional approaches to digitized prediction and product quality control is necessary. Additionally, this paper will discuss sufficient model performances to determine how the proposed DT-driven framework can be implemented to reduce defects, optimize operations, improve resource management and lead to optimal quality products. In total, CRM data innovation empowers reliable client cooperation across various channels of correspondence, includes versatile and web advances, client information the board and examination, process robotization however workflow innovations, combination with different frameworks and innovations, and an expansive set-up of applications, deals, administration, and accomplices, which may all be altered or on the other hand pre-configured for industry-specific requirements.

Keywords: Digital, Twin Technology, Transfer Learning, CRM Performance, Textile Industry.

2. Introduction

2.1 Research Purpose

This section of the paper presents the rationale for exploring the application of Digital Twin Technology in Pakistan's textile sector and outlines the research objectives through key investigative questions addressed in the subsequent sections. The integration of digital twin technology into Customer Relationship Management (CRM) holds the potential to transform how companies engage with their customers. By making virtual models of specific clients, businesses may learn more about what they like, how they act, and what they need. This deep understanding makes it easier to connect with customers in a way that is more personalized and effective. Digital twins can also help improve the whole customer experience by modeling client journeys to find problems and chances. Companies may make their customers happier, keep more of them, and eventually grow by adding technology to their CRM strategy. This will look at the pros and downsides of using digital twin technology in customer relationship management.

Motivation

The Pakistani textile industry operates as part of multiple sectors which implement digital solutions to enhance operational performance yet its essential position in national export values and GDP makes it an optimal choice for digital transformation advantages. As indicated in Table 1 and supported by the literature reviewed in this paper, there are at least five documented cases of practical digital twin implementation. The research benefits from using recent references which demonstrate the current state of the subject. However, these examples do not represent the full scope of digital twin applications, nor do they capture the technology's complete potential. A wide range of industries and organizations are increasingly adopting digital or virtual technologies to improve operational efficiency, gain better insights into product lifecycles, and enhance the overall value chain all with the goal of improving customer satisfaction, reliability, and information management (LeBlanc, 2020).

Table 1: *Applications of Digital Twin*

Examples of Implementation	Sources
Digital Twin in Surgery allows simulation of the healthcare surgical operations by utilizing sensors and computing devices to monitor the tasks.	(Ø et al., 2022)
Digital Twin in construction is used to make virtual models of buildings by using information collected from drones, sensors and other wireless technology, while the building is still in progress.	(Boje, Guerriero, Kubicki, & Rezgui, 2020)
Digital Twin is used in the sports industry to analyse a player's past performance data, combined with the recent metrics, to visualize their future performance	(Hou, Yu, & Song, 2020)
Manufacturing uses the Digital Twin to represent factories and processes or products to achieve business goals.	(Redelinghuys, Basson, & Kruger, 2020)
Formula 1 Twin in the racing industry simulates its cars and drivers to better adjust for improved performance during critical races.	(Mayani, Svendsen, & Oedegaard, 2018)

The textile industry in Pakistan, particularly yarn manufacturing plants, is composed of seven core departments. This complexity often hampers the achievement of production targets, especially in the presence of poor coordination, disruptions, or delays in the flow of information and resourcesThese plants need to make sure that all of their departments have as few problems as possible in order to fulfill market needs, especially when it comes to exports. To expand into new markets and stay ahead of the competition, you need to pay strict attention to the quality of your products and services (Gupta, 2013). A review of the pertinent literature indicates that yarn manufacturers encounter two significant challenges. First, it's really hard to uncover and research difficulties with things in stock, like yarn and looms. Second, there is an urgent need for better coordination and efficient production scheduling to be able to forecast difficulties and maintain production stable (Eirinakis et al., 2022). Industry 4.0 and the technology that make it possible are changing the world digitally, which is making it tougher for traditional production processes to stay up. With the use of digital infrastructure and the Internet of Things (IoT), it is now possible to always watch and research manufacturing activities (Tao, Zhang, Liu, & Nee, 2019). It's now possible to connect everything in the production process, such as people, machines, goods, and systems, because digital and physical systems can work together. Digital Twin (DT) technology has grown increasingly popular in both academic research and real-world use because of this (Cimino, Negri, & Fumagalli, 2019; Liu, Fang, Dong, & Xu, 2021). There are several ways to employ DT technology and its digital tools in production. It can correctly represent not only individual objects, but also whole production lines, shop floors, and even complex supply chains. Since its inception, the increasing utilization and popularity of DT have resulted in the incorporation of enhanced data and service layers into its framework (Tao et al., 2022). This ability to almost perfectly copy and analyze real products in the manufacturing environment has led to new ways and chances for growth (Becue et al., 2020; Eirinakis et al., 2022; Kritzinger et al., 2018).

A review of relevant literature reveals two principal challenges faced by yarn manufacturers. It's hard to find and fix problems with yarn and looms at first. Second, we need to improve the scheduling and coordination of production right away so that we can predict problems and keep output steady (Eirinakis et al., 2022). Because of Industry 4.0 and the technology that support it, the world is going through a digital shift that is making old ways of manufacturing things tougher to utilize. Digital infrastructure and the Internet of Things (IoT) have made it feasible to always watch and keep an eye on manufacturing processes (Tao, Zhang, Liu, & Nee, 2019). By connecting digital and physical systems, it is now feasible to connect all parts of the production process, including people, machines, products, and systems. Digital Twin (DT) technology has thus attracted considerable interest in both scholarly study and practical implementations (Cimino, Negri, & Fumagalli, 2019; Liu, Fang, Dong, & Xu, 2021). Digital tools make DT technology helpful for a multitude of different kinds of work. It can accurately show not only individual items but also entire production lines, shop floors, and complicated supply chains.

. Since its conception, the increasing popularity and use of DT have resulted in the enhancement of its structure to incorporate advanced data and service layers (Tao et al., 2022). The capacity to digitally copy and view physical objects in the industrial sector has unveiled new capabilities and developmental avenues (Becue et al., 2020; Eirinakis et al., 2022; Kritzinger et al., 2018)..

2.1.1 Research Questions

The objective of this research paper is to investigate Digital Twin Technology and analyze and evaluate its impact when applied to a textile manufacturing factory or workshop. This thesis seeks to answer the following research questions regarding this:

RQ1. How closely must the Digital Twin mimic its physical counterpart to generate greater value for the business?

RQ2. What enabling technologies are necessary to put in combination with the digital twin to implement its infrastructure?

RQ3. Which areas of CRM in yarn manufacturing factory can the Digital Twin impact positively?

2.2 Literature Review

2.2.1 Evolution of Manufacturing

Manufacturing is the process of changing raw resources into final goods through a sequence of planned steps. The manufacturing industry has seen a lot of technical progress throughout the years, such as the use of computers, automation, and data processing. Traditional industrial methods usually used a lot of energy, notably for utilities and production, and they often harmed the environment. Because of this, more and more manufacturers are moving toward cleaner, more digital ways of making things (Salam, 2021). For any field to go digital, basic processes like design, analysis, testing, scheduling, manufacturing, quality assurance, maintenance, and the use of digital tools like Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) systems must all work together and be in sync. Textile Sector of Pakistan

It makes up 57% of the country's total exports and provides a lot of jobs for people in the country. But new study shows that this industry has been growing more slowly in recent years. Some of the main reasons for this reduction are not enough money being spent on research and development, not having current facilities and equipment, and rising prices of making things. These problems, along with other things that aren't covered in this paper, have caused exports to go down and the sector's proportion of the worldwide market to go down. Cotton is also very important for the textile industry and the agricultural sector, since both are quite important to

Pakistan's economy (Ali, 2021).

The textile industry did see some excellent things happen during and after the COVID-19 epidemic, even though there were major problems. For instance, multinational purchasers transferred their orders to Pakistan because the global supply chain was having difficulty. This made production go faster so that it could reach its maximum point. The All Pakistan Textile Mills Association noted that the government's safety measures also helped the industry get back on its feet. This full capacity did not include the textile plants that had to close due of the virus.

Orders from China, Bangladesh, and India had been redirected to Pakistan. The textile industry is doing well, but it is important to take advantage of these chances by updating and modernizing processes to boost productivity. To do this, it is now very important to look for new technologies and advances in the global market and define performance standards based on those (Ali, 2021). In the textile industry, turning yarn into fabric comprises getting the raw materials, storing them, spinning them, weaving them, dyeing them, checking their quality, and then packaging and sending them. This industry is naturally complicated and has problems including a lot of different products, unexpected demand, customisation needs, and long production cycles, all of which make it unstable. The production processes vary quickly every day, therefore new orders or changes in fashion and design trends need to be dealt with quickly. These characteristics make operations even more complicated when they are added to conventional production schedules (He et al., 2021; Yin et al., 2021). Also, yarn production is prone to errors or breaks, making it hard to make a product that is free of flaws. Problems like uneven formations induced by the sticky nature of cotton or fly contamination in the ring spinning sector might cause faults. Because of this, it is still hard to make sure that ring spinning is perfect. To lessen these hazards, it is important to set up a strong monitoring and prediction system (Gupta, 2013).

2.2.2 Digital Twin Definition

A product goes through several design changes from its inception to the decline phase (Peñaranda, Mejía, Romero, & Molina, 2010). These changes are translated into variations in assembly material, component designs, sources of procurement, or manufacturing strategies. A change in the strategy for manufacturing then further leads to tools, programs, or automation being replaced, and incurring changes in the product life cycle. This end-to-end integration of the value chain required a defined and integrated Product Lifecycle Management (PLM) system. The digitization and desegregation of this value chain led to the creation of a digital version of the physical products and processes, which is labeled the 'Digital Twin'(Tao et al., 2018). According to Ivanov, Dolgui, and Sokolov (2019), the present research is supportive of the "Digital Twin" notion, in the realm of Industry 4.0. As explained by Fuller, Fan, Day, and Barlow (2020), the Digital Twin (DT) is a digital clone of any physical object, in real-time, in which the actual parts are mirrored in a virtual setting and updated iteratively from numerous sources for different purposes. IoT technologies and related systems are designed to capture real-time data using edge computing devices and smart gateways. The Internet of Things provides access and connectivity to intelligent data and is associated with digital twin (DT) and digital models that are virtual representations of their physical counterparts. In general, cognitive computing, which encompasses technologies such as big data, artificial intelligence (AI), machine learning (ML), deep learning (DL), and cognitive algorithms, mimics the human psyche in a computer model using DT technology. DT consists of physical and digital products, including links between two products (Alizadehsalehi & Yitmen, 2021).

2.2.3 Digital Twin Origins

The idea of "twins" came about during NASA's Apollo program in the 1970s, when physical copies of spacecraft were made to show how they were doing and what was going on in real time (Hu, Zhang, Deng, Liu, & Tan, 2021). Michael Grieves came up with the formal idea of the Digital Twin (DT) in 2003. He called it a "virtual digital representation equivalent to physical products" (Grieves, 2015). NASA accepted and put the DT idea into action in 2012. This linked ultra-precise simulations with vehicle health management systems, maintenance records, and historical fleet data. NASA could keep an eye on the performance and lifespan of physical assets with an unmatched level of reliability and security because to this integration (Glaessgen & Stargel; Tuegel, Ingraffea, Eason, & Spottswood, 2011).

The idea of the Digital Twin has been around for more than ten years, but it has only recently gained a lot of scientific interest. This is mostly because technologies like the Internet of Things (IoT) have become more mature and can now be used effectively in business and industry. The concept of DT has evolved over time across multiple fields, resulting in at least two independent interpretations (Negri, Fumagalli, & Macchi, 2017). This broad view is the basis for the current study.

2.2.4 Digital Twin in Literature

A lot of businesses have thought about how to employ Digital Twin (DT) technology in the real world. It helps companies make a digital model of a product that shows how it will look and work across its whole life. This helps detect flaws sooner, correct physical problems faster, and make better guesses about what will happen, all of which makes customers happier (Sahu, Agrawal, & Kumar, 2022). The DT model covered the whole life cycle of a product, from when it was made to when it was thrown away. It showed how a product will look and work in both the present and the future (Latif, 2020).

Nikolakis, Alexopoulos, Xanthakis, and Chryssolouris (2019) suggested the amalgamation of Digital Twins (DT) with a comprehensive Cyber-Physical System (CPS) to improve human-centric manufacturing processes via virtual planning and simulation. Schroeder, Steinmetz, Pereira, and Espindola (2016) contended that Automated Machine Learning ought to be employed to improve Digital Twins. They looked at how well it worked to control the flow of data between systems that were connected to each other on the network. Tao and Zhang came up with the idea for a "Digital Twin Workshop" in 2017. This workshop's purpose is to show you how to apply predictive management and monitoring on hard-to-use equipment. Many large organizations throughout the world, such as PTC, ANSYS, GE, and Siemens, have looked into other methods to employ the Digital Twin architecture (Dutta, Kumar, Sindhwani, & Singh, 2022). Digital transformation has several advantages for many businesses, including faster time to market, more effective operations, cheaper maintenance costs, increased user engagement, and better information integration (Tao, Zhang, Nee, & Tao, 2019).

2.2.5 Digital Twin Application in CRM in Manufacturing

To make sure that physical and virtual systems work together, you need mathematical models, real-time data processing, sensed data, and smart devices that can talk to each other. The main job of Industry 4.0 manufacturing systems is to use these qualities to predict and improve the production system's performance in real time over its entire life cycle. A digital twin is a concept that is talked about in a lot of different ways in the literature, but you can still get a fundamental notion of what it is. It is essential to distinguish between terms such as Digital Model, Digital

Shadow, and Digital Twin according to their efficacy in relation to their physical counterparts. Kritzinger et al. (2018) assert that a digital model constitutes a component of a digital twin. The manual transmission of data between the digital and physical models is what makes it happen, which inhibits changes from happening in real time.

On the other hand, the Digital Shadow means that data is automatically moved from the physical model to its digital counterpart. However, any changes to the digital model must still be input by hand. The actual Digital Twin makes it possible to automatically exchange data in both directions, making sure that any changes to either the physical or digital entities are recorded right away. The system uses real-time data from industrial processes, sensor inputs, and client communications to provide you a full view of your connections with customers. Businesses can use digital twin technologies to tailor customer experiences by predicting what they need and want. By looking at how customers use and buy items, manufacturers can find ways to boost upselling and cross-selling, reduce churn, and build customer loyalty.

Using CRM and Digital Twin technologies together makes running a firm easier. Manufacturers may find ways to improve their supply chains, make their operations more efficient, shorten lead times, and improve the quality of their products—all while lowering costs—by keeping an eye on how customers use and interact with their products. Digital twin technology also makes it possible to monitor client input in real time, which lets producers quickly fix problems and make clients happy. This leads to better customer service and faster problem solving. Using digital twin technology in CRM has many benefits, such as better customer service, faster business operations, and feedback that is given right away. This technology is a must-have for businesses who want to stay competitive in a market that is always changing.

2.2.6 MES and MBSE

The Digital Twin is also expected to be integrated to manufactured products so that each has its own DT. As mentioned by Contan, Dehelean, and Miclea (2018) and Körner et al. (2019), each industrial automated process finds its foundation in the Automation Pyramid, which is a unified structure with five layers. Figure 1. below shows the framework considered, with the automation period on the left, and the production management level on the right. It also consists of the Manufacturing Execution System (MES).

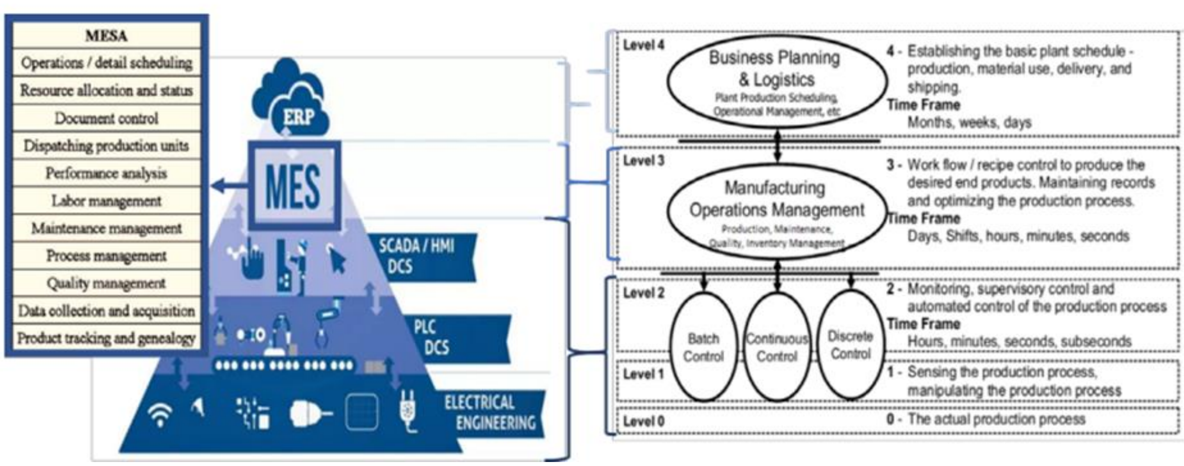

Figure 1: *The Automation Pyramid Framework (Govindaraju & Putra, 2016; Shrouf, Ordieres, & Miragliotta, 2014).*

As evident from the structure shown above, the MES leads the manufacturing process, where all the production steps in the system are monitored in a centralized manner. Among these functions, as identified by MESA, there are some that are directly linked to production, such as scheduling and quality control, while others such as resource management are cross functions. The production planning and control systems have the key requirement of being able to provide a balance among the varied production system requirements (Deradjat & Minshall, 2018). Lead time, production cost, and customer requirements are some typical requirements that are directly incorporated into the key performance indicators (KPIs) for production. However, the balancing of the production plan is a time consuming process which may have latent consequences (Fatorachian & Kazemi, 2021). Most of this is attested to the variability in orders throughout the factory. This, coupled with limited machine and employee competencies, can act as constraints on the production process, which further confines the cycle times (Lam, Toi, Tuyen, & Hien, 2016). Manufacturing systems are required to carry out pre-set scheduled operations and incorporate the changes continuously. The manufacturing system is normally controlled by the MES, as stated by (Rosen, von Wichert, Lo, & Bettenhausen, 2015). The enterprise would be required to develop and implement the digital twin model at a workshop level. The simulation model would be dynamic, and based on the mixture of IoT and Big Data, therefore it would include all the details of its physical counterpart. With the help of sensors information such as real-time changes are recorded, due to the connection with the physical entity. This is then connected to the MES to carry out a continual updating process and allow for the iterations to be executed (Shuguang & Lin, 2020).

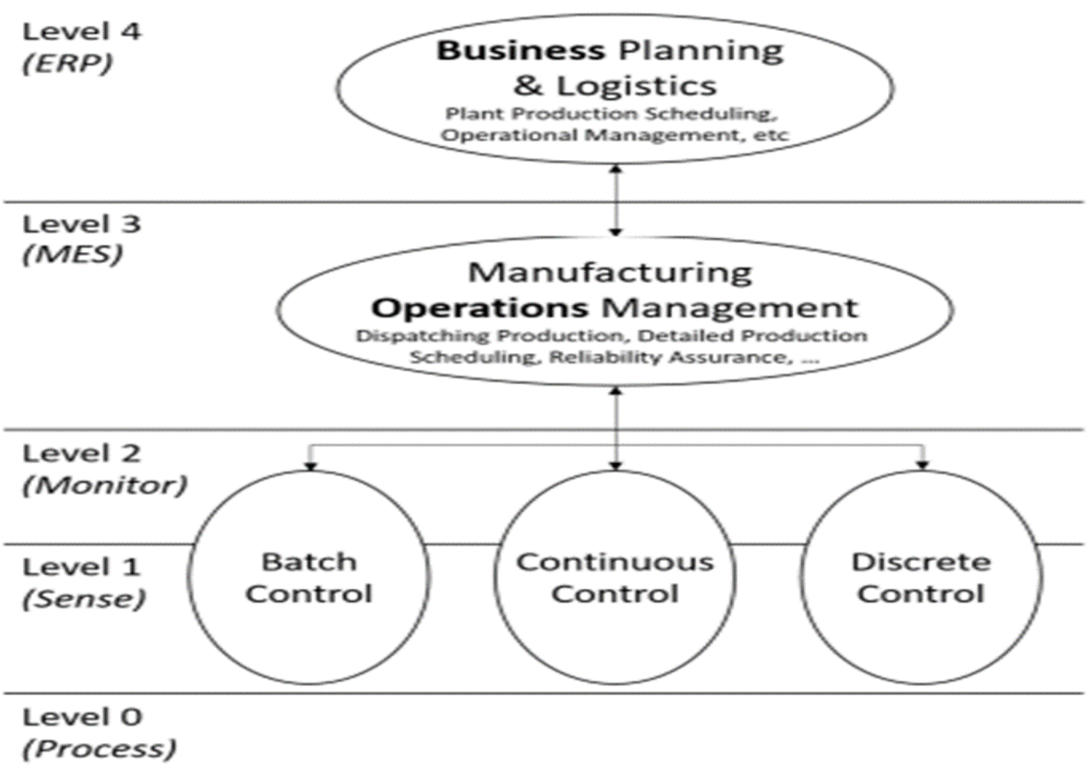

Figure 2: *ISA 95 enterprise control system integration framework*

ISA-95, illustrated in Figure 2 above, is a framework designed for integrating enterprise and control systems. Its purpose is to facilitate seamless integration within an organization across manufacturing operations, business processes, and other related activities. The framework outlines five hierarchical levels of operation. The highest level, Level 4, focuses on logistics and business planning and is where systems like ERP or SAP are typically implemented. Level 3 centers on the management of manufacturing operations and involves the use of Manufacturing Execution Systems (MES). Levels 1 and 2 are primarily concerned with monitoring and observation activities. The lowest level, Level 0, represents individual physical processes such as milling or turning. This framework serves as a guideline for system integration within organizations at each level (Hedberg Jr, Helu, & Sprock, 2018).

In the manufacturing sector, Digital Twin (DT) technology is also expected to play a pivotal role in Model-Based Systems Engineering (MBSE) in the near future. Together, DT and MBSE hold the potential to be applied throughout the entire lifecycle of any system (A. M. Madni, C. C. Madni, & S. D. Lucero, 2019).

Model-Based Systems Engineering (MBSE) is the planned use of modeling to help with Systems Engineering (SE) duties at all stages of a system's life cycle. Model-Based Systems Engineering (MBSE) is a well-known, structured, and cross-disciplinary method that brings together the needs of all system stakeholders, both technical and business, to make sure that the system is of high quality, can be traced, and can grow. Sheurer (2018) talks about the main ideas behind a few SE frameworks and shows a novel model called the "Diamond" Vee (Figure 7). This concept is a good starting point for building an MBSE framework just for Digital Twins.

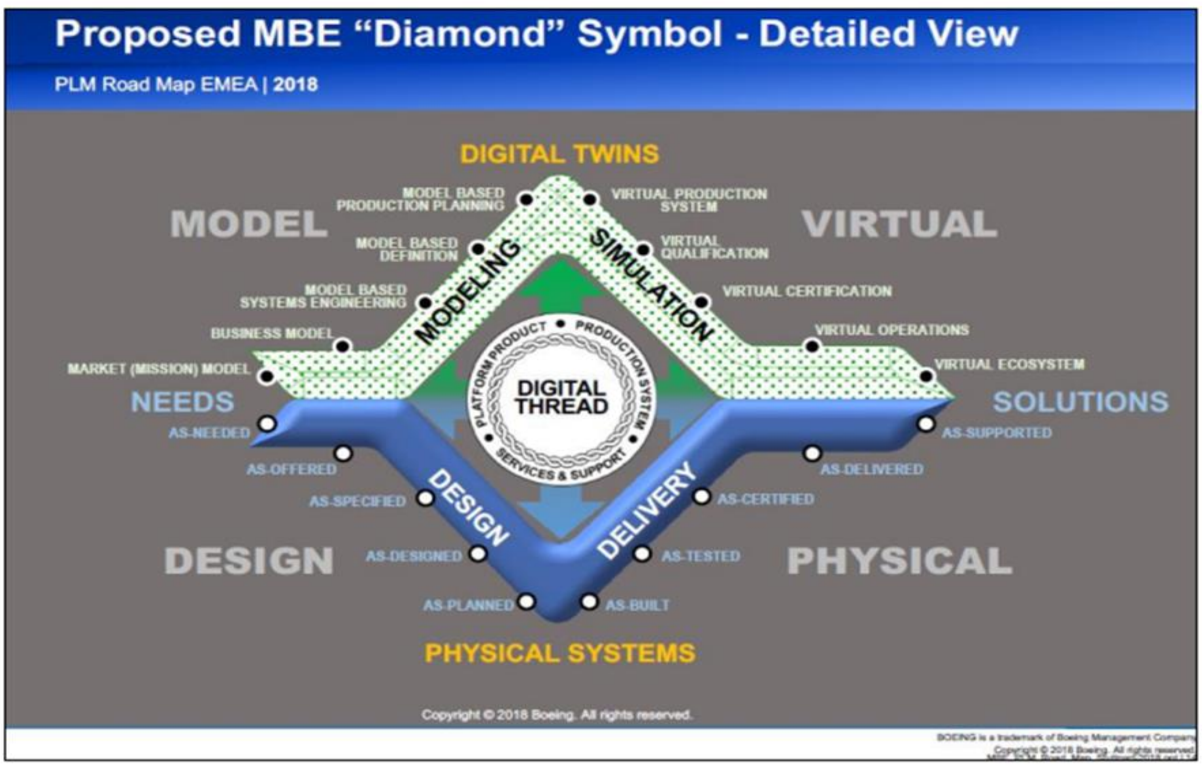

Figure 3: *MBSE- Digital Thread Framework*

Schluse et al. (2018) contend that Model-Based Systems Engineering (MBSE) can function as the underpinning for the digital thread. You can use the data from IoT in system simulations to look at many ways that things can go wrong, which lets you make design changes over and over again. Model-Based Systems Engineering (MBSE) methods like Design Failure Mode and Effect Analysis (DFMEA) can help manufacturers connect the digital twin to their processes, expected failure modes, and data in real time, according to A. M. Madni, C. C. Madni, and S. D. J. S. Lucero (2019). If it uses the correct MBSE technology, the digital twin can do 3D simulations and give you important information (Azad M Madni et al., 2019).

2.2.7 Digital Twin and The Digital Thread

The Digital Thread is a data-driven framework that connects the flow of information that the Digital Twin controls. This makes it easier for the product to go from being made to being thrown away (V. Singh & Willcox, 2018). The Digital Thread idea came from the aerospace industry, where integrated systems engineering was first used to handle product data digitally. This method includes logistics, production methods, distribution plans, and 3D CAD models.

This integration fosters optimal synchronization between the physical and digital twins across operations. Furthermore, the Digital Thread enables feedback incorporation, multi-dimensional data fusion, and iterative decision-making, ultimately driving process flow optimization (Shuguang & Lin, 2020).

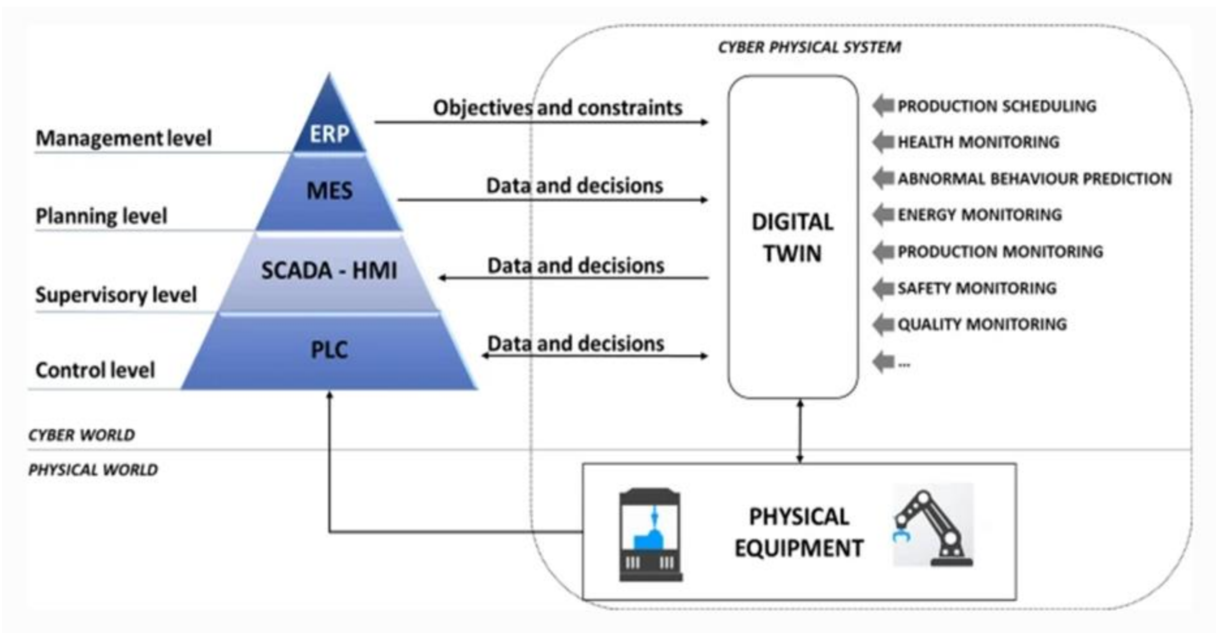

Figure 4: *Digital thread and MES implementation Framework (Negri et al., 2021)*

In addition to this, the MES is also compatible with the Digital Thread. The framework shown above presents how all decisions such as schedule routing can easily be shared across the manufacturing system, on the basis of industry standards. This would also allow the decisions to be made on the basis of evaluated and predicted capabilities or status of the physical processes in the manufacturing system, as well as other information such as process constraints, delivery schedules etc. from control databases such as ERP, MES or quality management systems (Mohammed, Arbo, & Tingelstad, 2021).

2.2.8 The Intelligent Digital Twin

A crucial component of any Digital Twin application is the digital representation of its assets—such as CAD models, simulations, software models, and more—though the specific requirements vary depending on the actual assets and their intended purposes (Boschert & Rosen, 2016; Negri et al., 2017). Digital Twins have a wide range of applications in manufacturing systems, including planning, maintenance, control, and fault diagnosis (Kritzinger et al., 2018). One key advantage is that a physical asset is not always necessary, as testing, programming, and optimization can be performed virtually through advanced computing power (Zipper, Auris, Strahilov, & Paul, 2018).

According to Jazdi, Ashtari Talkhestani, Maschler, and Weyrich (2021), an intelligent digital twin can study and assess its surroundings to find novel ideas and insights.

Intelligent Digital Twins are employed to identify problems, detect errors, manage processes flexibly, and optimize sequences (Talkhestani et al., 2019). The intelligent Digital Twin operates by observing and exploring its environment using operational data gathered from sensors or actuators. This data is then analyzed alongside existing Digital Twin models to extract new knowledge that goes beyond the explicit information contained in current models (Kritzinger et al., 2018). However, to date, implementations have largely been isolated cases that do not yet fully incorporate reintegration or feedback loops into the Digital Twin system (Benjamin Maschler, Braun, Jazdi, & Weyrich, 2021).

2.2.9 Deep Transfer Learning and the Digital Twin

Transfer learning in machine learning involves leveraging what you learnt or did well in one task to do better in another activity that is comparable (Pan & Yang, 2010). Numerous fields, including visual recognition, healthcare, and communications, have extensively examined the concept (Weiss, Khoshgoftaar, & Wang, 2016; Zhuang et al., 2019). Recently, many have been interested in how it can be used in business (B. Maschler & Weyrich, 2021; H. Tercan, Guajardo, & Meisen, 2019). Transfer learning has been extensively examined in domains such as email spam filtering, medical imaging, and speech recognition (Durgut, Aydin, & Rakib, 2022; R. Zhang, Xue, & Liu, 2019; Y. Zhang & Yang, 2017), although its complete potential in industrial automation remains inadequately investigated.

Transfer learning can help with two big problems that come up in factories. It is difficult to collect large, relevant datasets for training at first since there aren't many equivalent pieces of industrial gear, there are strict restrictions regarding data protection, and organizations can't readily cooperate together (Hasan Tercan et al., 2018). Second, algorithms need to be retrained and data needs to be added to them over and over again because industrial environments, processes, and systems are always changing (Benjamin Maschler, Huong Pham, & Weyrich, 2021; Müller, Jazdi, Schmidt, & Weyrich, 2021; Hasan Tercan et al., 2018). Transfer learning helps solve these challenges by enabling algorithms learn from datasets that are relevant to the current activity and from actions that happen at different stages of the product lifecycle. For instance, Canizo, Triguero, Conde, and Onieva (2019) built an algorithm for identifying faults that might work with many different kinds of data. Hasan Tercan et al. (2018), on the other hand, built a quality management algorithm that was already trained for manufacturing operations. Quality management in manufacturing is to create ways to check the quality of products, like finding defects after they happen and predicting defects before they happen utilizing constraints, regression, and classification tasks (Schlegel, Briele, & Schmitt, 2019).

Also, DTL can predict and stop machinery breakdowns, which improves the quality of products and industrial settings (Deebak & Al-Turjman).

2.2.10 Digital-Twin Assisted Fault Diagnosis and Predictive Control

According to Rosen et al. (2015), DT is a new model that is gaining fame for its potential support towards the development of intelligent manufacturing. It replicates and plots out the entire lifecycle of a product via realistic and progressively enhanced mock-up models. This helps to reduce the cost of designing and maintenance while improving efficiency and quality of manufacturing (Rosen et al., 2015). However, in Y. Xu, Sun, Wan, Liu, and Song (2017), the authors argue that while the manufacturing process has become more complex and intelligent, the security and reliability have come into question. Any minor failure during the production process can result in huge losses, therefore, a fault diagnosis is critical in a smart manufacturing system (Y. Xu et al., 2017). The current studies highlighted in this literature review are more focused on the conceptual models and crucial technologies that are based on the digital twin. Digital twin-based fault diagnostics has always been thought of as a small part of production. Many research has not looked closely at the design, algorithm, and mechanisms of the fault diagnosis model. The manufacturing sector has changed the way businesses communicate with and build relationships with their customers by using digital twin technology and its predictive control feature in Customer Relationship Management (CRM). Digital twin technology lets you keep an eye on and analyze industrial activities in real time by making virtual copies of physical assets.

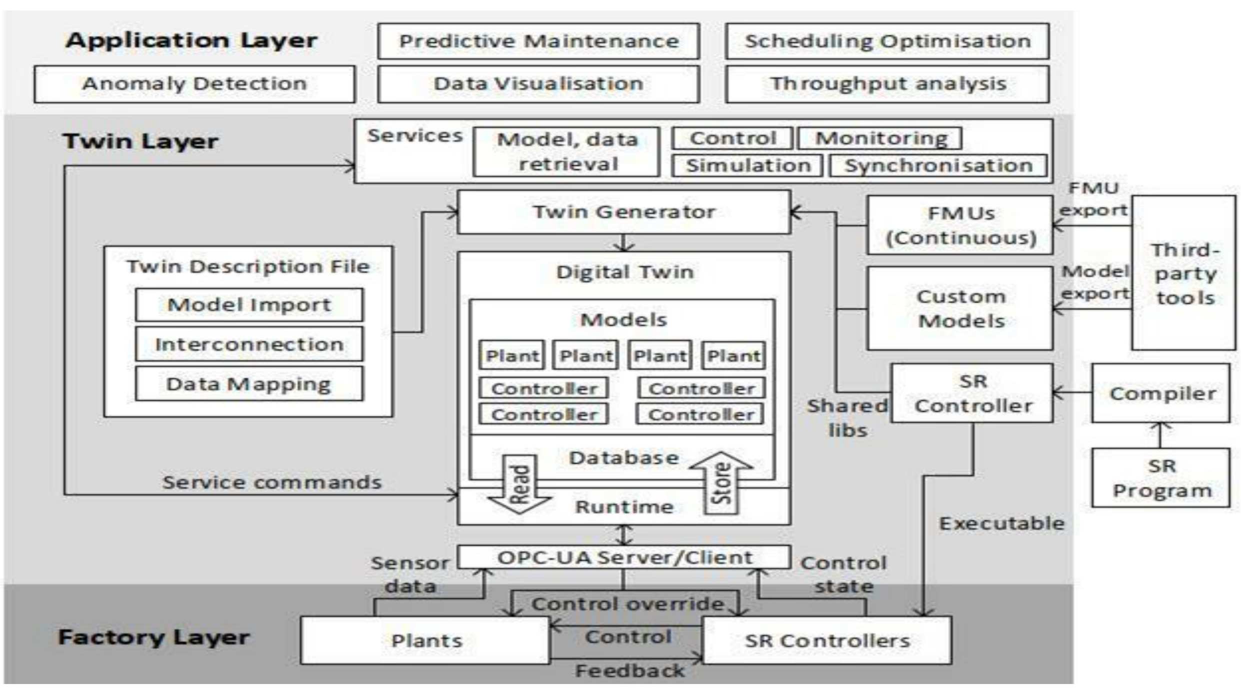

Figure 5: *Digital Twin application in Factory Framework*

Krdžalić and Hodžić (2019) in their paper state that the Human Machine Interface (HMI) requires the monitoring of real-time machinery processes during the maintenance activities. When the physical data is analysed it makes use of the sensor technologies to identify any signs of defect or faults (Krdžalić & Hodžić, 2019). The framework shown in the figure above, demonstrates the use of the Digital Twin assisted Fault Diagnosis (DT-AFD) using the DTL model, which will basically combine the Digital Twin technology with the Deep Transfer Learning to assist the detection of defects and faults for enabling an agile manufacturing approach. The Digital Twin is applied to change the pattern of fault diagnosis to provide an improved interaction between the physical and virtual spaces (Lei, Jia, Lin, Xing, & Ding, 2016). The DT-AFD model categorizes two critical phases which are proactive maintenance and intellectual development. The former includes techniques to test, authenticate and improve the virtual space. While the former involves the construction of a digital designing and manufacturing platform in order to exploit resources used, industrial standards, and data processes (Deebak & Al-Turjman, 2021). Once the virtual space is built and is satisfactory the physical entity is developed and attached to its digital counterpart. Simultaneously, DTL plays its part by forming a diagnosis model by shifting the knowledge from the preceding phase. This enables the model to accurately predict the performance evolution in the initiation of the manufacturing process but also allows adaptation to the changes. However, despite the inclusion of potential design defects in the development phase, unprecedented breakdowns may occur.

Due to the risk of such cases, Predictive control is necessary, that focuses on forecasting problems early on, and preventing anomalies and disturbances. This is done with the help of a smart control component, which allows fine-tuning and adaption of its behaviour according to the environment based on machine learning and deep data analysis (Deebak & Al-Turjman, 2021). Digital Twin technology is used in this preventative maintenance as well, where it enables the forecasting of the assets status to reduce the number of operations and allowing longer intervals between them in a manufacturing system (Longo, Nicoletti, & Padovano, 2019; Vathoopan, Johny, Zoitl, & Knoll, 2018). Since the Digital Twin is a virtual image of the entire MES, it allows the real-time monitoring of performance, and can alert to any repairs or maintenance that need to be carried out. This helps maintenance processes to be scheduled proactively, and downtimes can therefore be avoided (Hosamo, Svennevig, Svidt, Han, & Nielsen, 2022; Poppi, Bales, Haller, & Heinz, 2016). The Digital Twin keeps track of the physical counterpart's mortality and operational life, based on the real-time data of wear and tear. Through simulations, it can then estimate the how long the working life of the machinery is, and can create a proactive maintenance schedule based on that. That is, predictive maintenance is deployed to determine how long the physical object can last, and this is useful for the machines used in the manufacturing sector, as downtime and breakdown can be avoided (Azad M Madni et al., 2019).

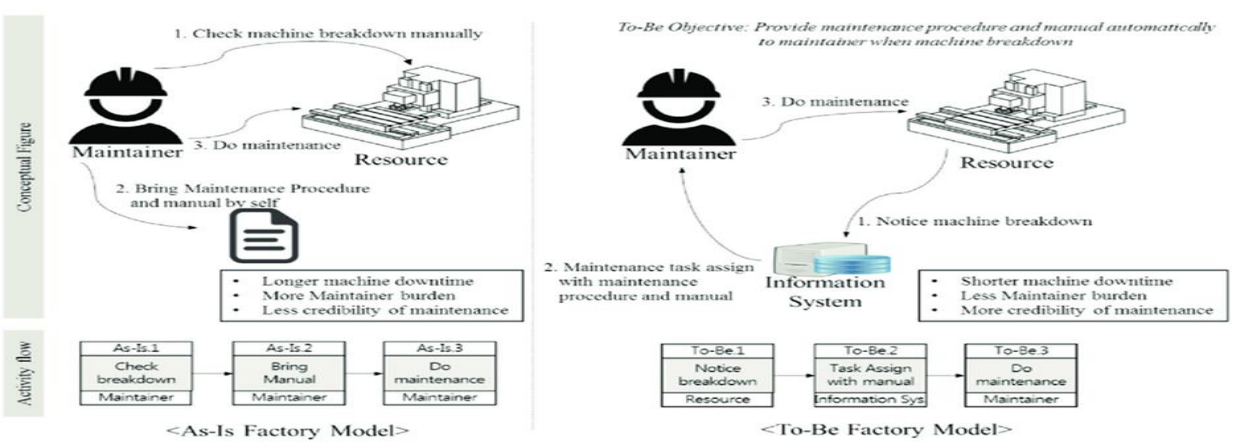

Figure 6: *DT-AFD Framework*

2.2.11 Application of DT for CRM in Textile Sector

3 Overview of Research Framework

This section will define the scope of this research, methodology and the outline of the research conducted.

3.1 Scope Definition

For the purpose of this research, the scope definition aims to describe the application of Digital Twin in the manufacturing unit of a textile factory. The main objective of this paper is to determine the major applications, potential enablers and usages, practical implementations, advantages and challenges associated with DT and its incorporation into CRM in the manufacturing set up. Additionally, the research gap identified, and the current works limitations help to identify improvement opportunities and future research areas. Consequently, it was observed that while the process of implementing DT in Yarn manufacturing may look straightforward, it is actually highly complex due to lack of adequate equipment, and susceptibility to failures and disruptions. Furthermore, it must be realized that a facility performing well in its first year of digitization may or may not continue to do so. Unprecedented events such as the pandemic may also end up shutting down the enterprise, therefore a sustainability plan is critical as well.

Digital twin technology is a novel notion that is transforming a lot of different areas, but the textile industry is the most affected. Digital twin technology in Customer Relationship Management (CRM) has transformed the way textile companies talk to their customersBy creating a virtual version of the real thing, digital twin technology enables textile companies to provide a consistent experience for their customers. This enables them to provide their customers with solutions that are specifically designed to meet their demands.

The textile business relies heavily on customer relationship management (CRM) activities, which are strengthened by digital twin technology. Textile companies can use digital twin technology to create a digital model of every product that displays consumers its features, appearance, and operation. This reduces returns, increases customer satisfaction, and assists customers in making informed decisions.

Textile companies can also observe their customers' behavior and preferences thanks to digital twin technologies. They can then use this information to personalize their interactions with clients. This can be accomplished by using sophisticated algorithms to determine the needs and desires of the client and by analyzing customer data in real time. This helps textile companies better connect with their customers by making marketing plans more successful and focused.

In summary, both textile companies and their clients can gain greatly from the use of digital twin technology in CRM. By providing customers with a virtual version of the actual products and using intelligent analytics to monitor what customers do and enjoy, digital twin technology helps textile firms make shopping easier and more personalized for their customers. Customers are happy and more inclined to return as a result.

3.2 Research Methodology

The study looks at how well digital technology can be utilized to find problems and do predictive maintenance in a textile production setting to keep machines running well.

The Conceptagon model (shown in Figure 7) is used in the study to look at the Digital Twin production system framework. This model gives a complete picture of the architecture of processes and functions, making it a useful tool for figuring out both the problem and the solution areas. The model has 21 qualities that are grouped into 7 triads. This makes it easier to understand how all the parts of the system work together and how they work (Boardman, Sauser, John, & Edson, 2009).

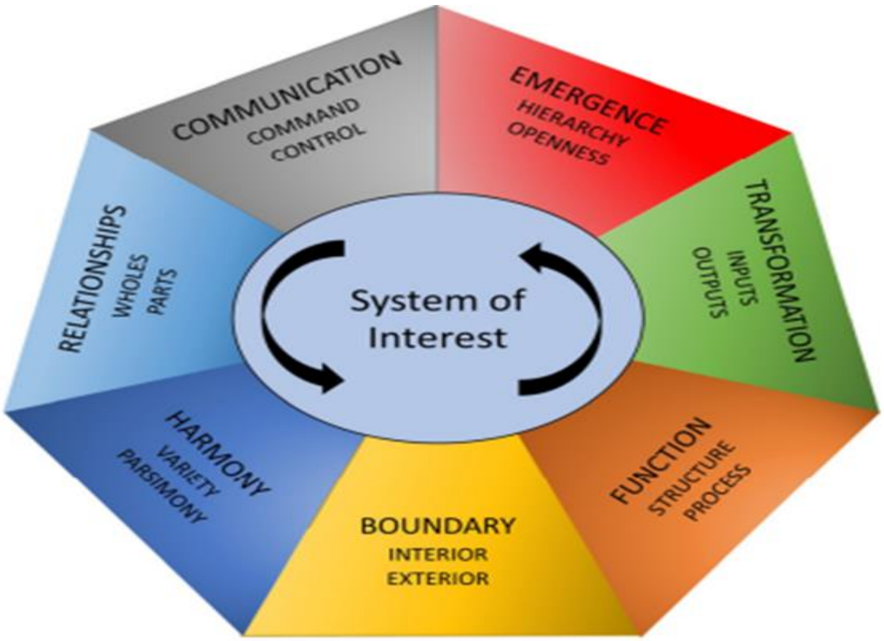

Figure 7: *Conceptagon Framework*

This research paper intends to make use of the conceptagon model to analyse the implementation of DT in Yarn manufacturing, however, it is important to add that this is not an official method for its usage.

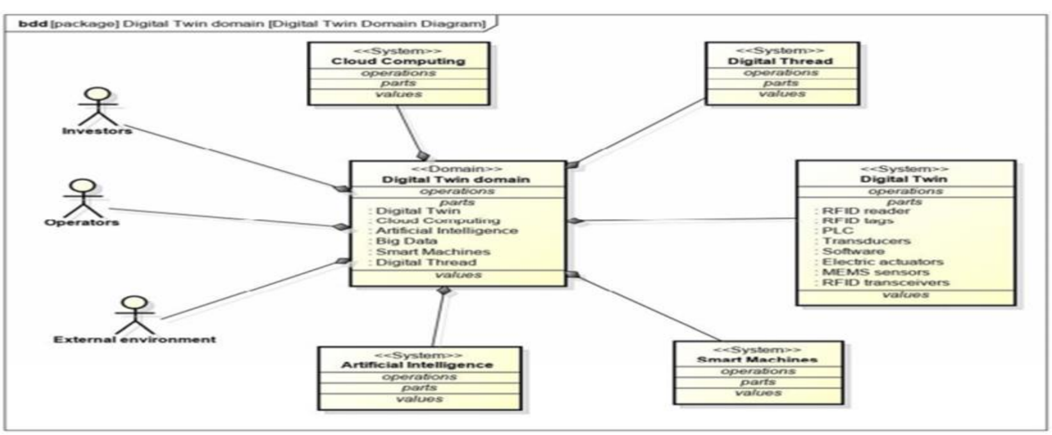

Figure 8: *Digital Twin Domain Model*

The interior level of DT in the manufacturing system will present varied components, as shown in Figure 8 above. This consists of RFID tags and readers, electric actuators, MEMS sensors, transducers and switches. On the other hand, the exterior of DT is the actual manufacturing system which is a bigger domain that becomes the subsystem, this includes other components such as digital thread, artificial intelligence, and smart machines, as well as relevant stakeholders (Loaiza & Cloutier, 2022).

This paper also analyses a systemigram for determining the relation between the DT model and yarn manufacturing system. This model considers the systems readiness level, MBSE and digital transformation necessary for the implementation of DT. Figure 9 shows the systemigram for the conceptual understanding of DT in manufacturing (Loaiza & Cloutier, 2022).

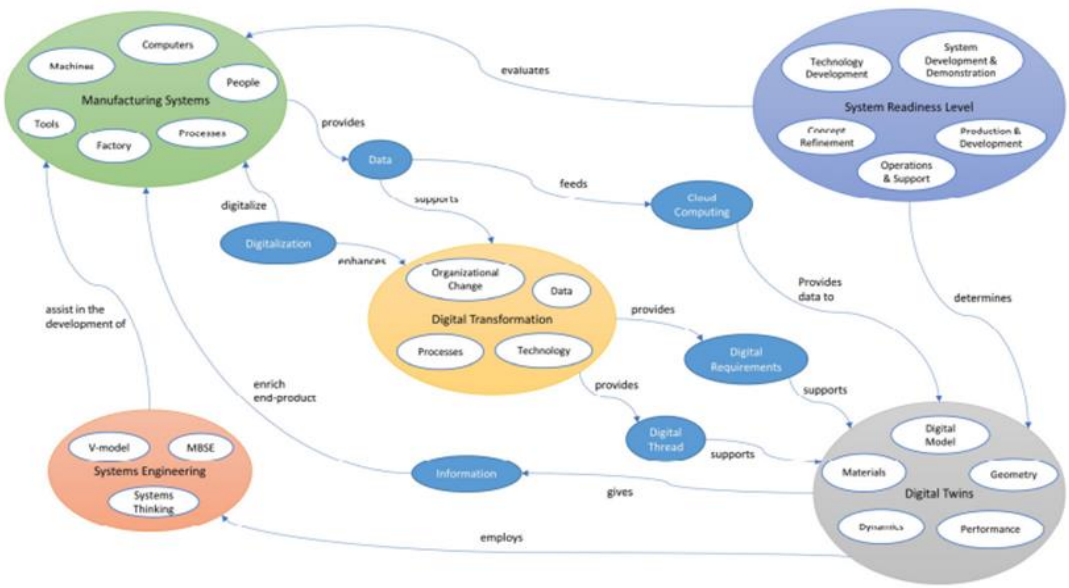

Figure 9: *Systemigram for conceptual analysis of DT in a manufacturing systems.*

In the paper a simulation is applied to replicate the patterns in a spinning department in a garment factory. The physical objects in the factory are constructed and replicated in a virtual space using the 3D modelling, data from digital thread, task programming and process optimization. The controlling system is then used to realize bidirectional communication of information, as well as flow of resources and data.

Figure 10: *The unified design concept of the intelligent manufacturing system*

Based on the varied production tasks, the method for collecting information to arrange the layout of the work area and activities related to production is 'mutually independent,' during data processing, such as when implementing the MES. However, the information flow from these silos can be disrupted or not done dynamically due to various reasons. To improve the integration of information, real-time flow and interdependence, the Digital Twin technology is introduced to further absolve and avoid downtimes, defects or other production disruptions.

For the physical evaluation, the factory, detection equipment, interface layer and physical modelling is used, as demonstrated in figure 2 below:

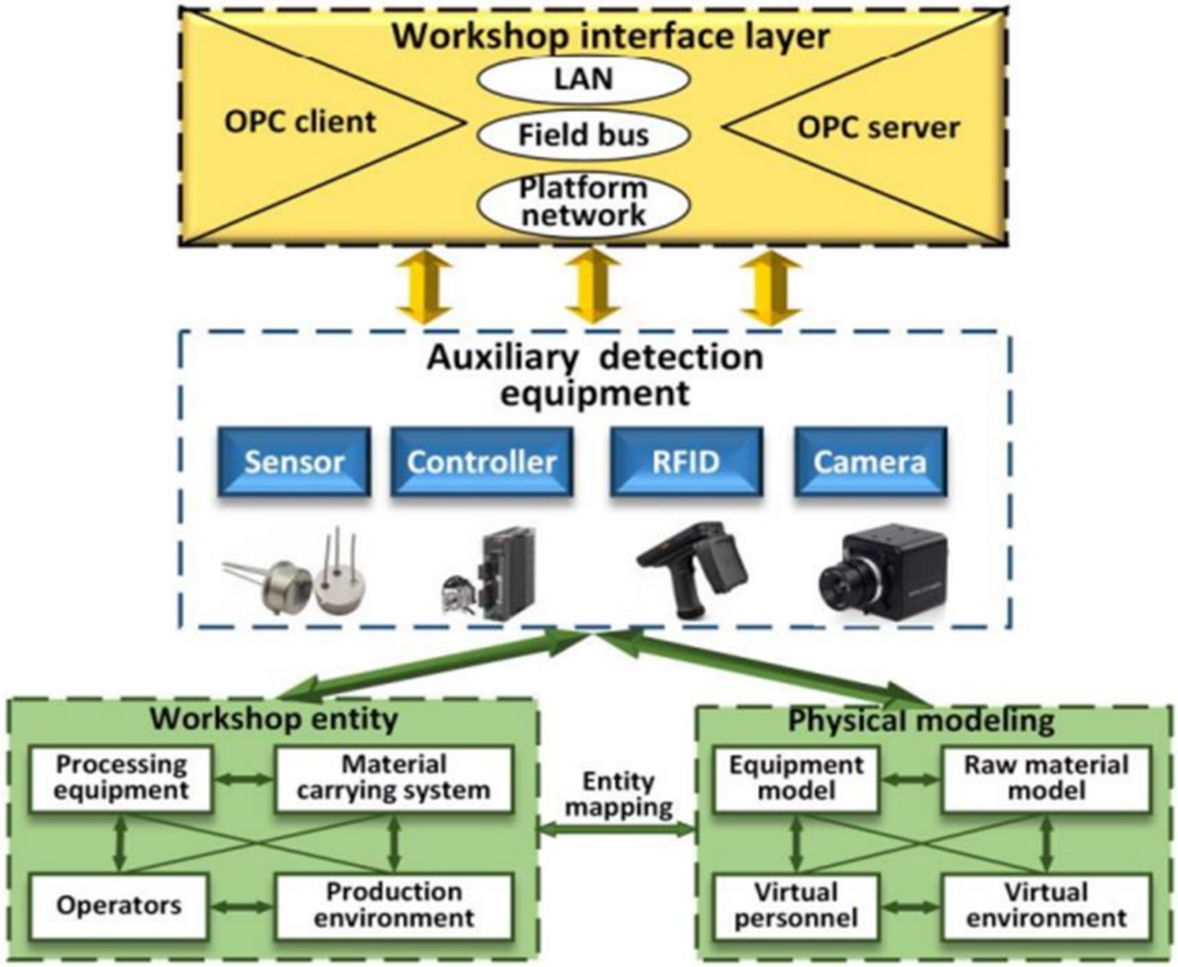

Figure 11: *Physical evaluation*

Additionally, research was done to determine the connection between machine maintenance and quality control. As shown in figure 11, a diagram was constructed to better understand the connection and to determine how the digital technologies being explored in the paper can fit into it.

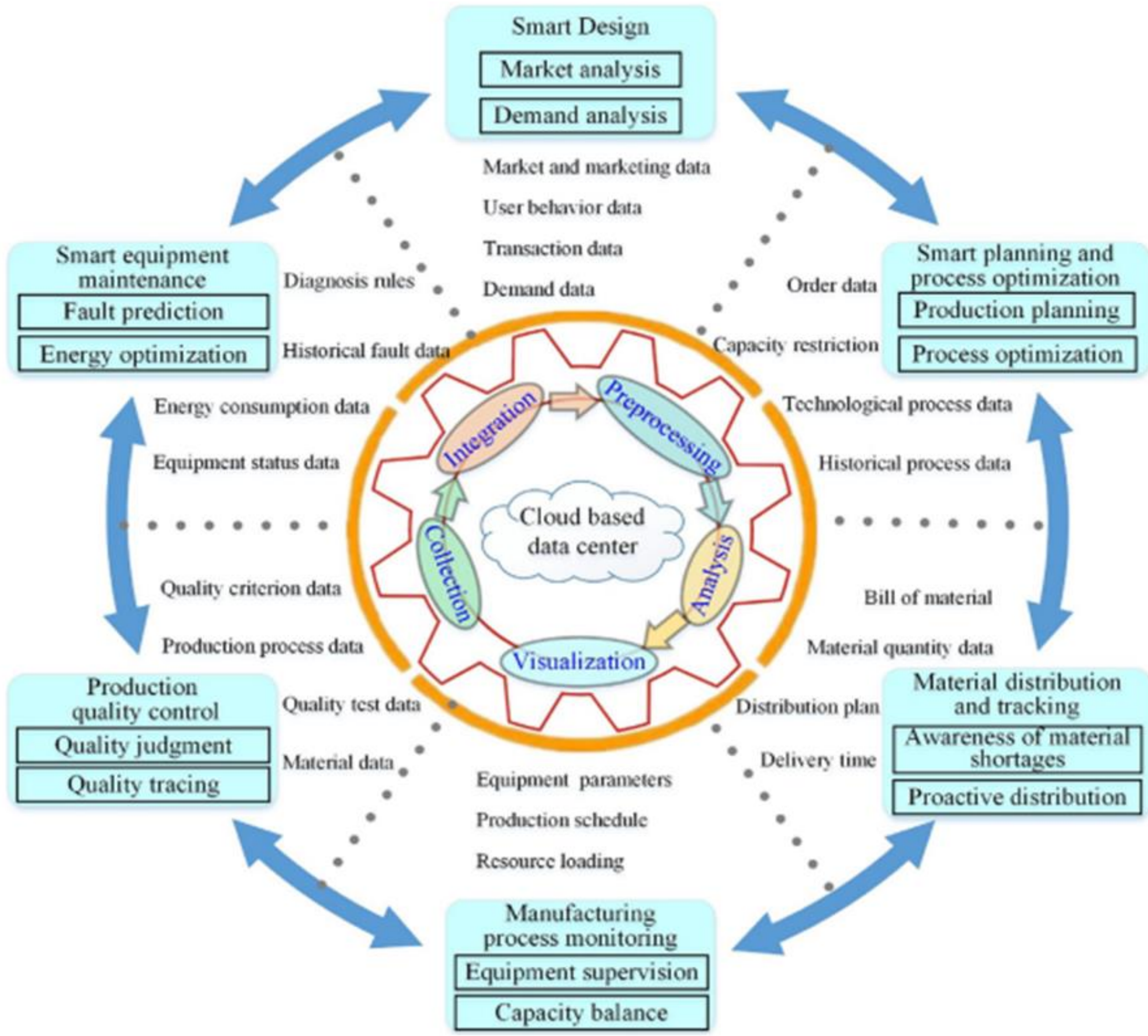

Figure 12: *Conceptual implementation of DT-AFD and predictive maintenance*

There is still a lot of research being conducted on the fault diagnosis, predictive control and DTL concepts. However, they focus more on the general perspective rather than practical implementations.

That being said, it must be noted that the design of the DT processes requires a holistic approach through the ontological and epistemological dimensions. According to Sacks, Brilakis, Pikas, Xie, and Girolami (2020), ontologically the DT is a combination of various entities of production information. The authors considered manufacturing the flow of design information such that the productive assets are viewed as data carriers (Sacks et al., 2020). Suh (2001) stated that information designing is based on the axiomatic design theory, and includes data on functional requirements, design parameters and solutions etc. Epistemologically, the twins are utilized by personnel to create and execute production systems and contribute to knowledge generation by comparing expected outcomes with actual results. This is best described through the Plan-Do-Check-Act (PDCA) cycle, and personified in varied functions in production management (Tzortzopoulos, Kagioglou, & Koskela, 2020).

This research makes use of a quantitative approach s well, to evaluate the views of Pakistan's Textile Industry, on the concept of digital twin technology, which is fast gaining popularity around the world. For the purpose of quantitative data collection, a questionnaire was designed with a four-point readiness evaluation derived from previous studies. The study is exploratory in nature, which includes respondents belonging to the large enterprises in Pakistan's Textile sector, located in Faisalabad. The motivation behind choosing the textile sector is because it contributes more than forty percent to the country's GDP (Wadho & Chaudhry, 2018). Based on the report issued by the State Bank of Pakistan, around 1,900 SMEs are operating in the textile industry, however, the number would have increased significantly by now (Pakistan, 2011)

Respondents in the paper include entrepreneurs, SC executives and managers, and a structured questionnaire was given to collect responses. Approximately one-thousand questionnaires were distributed, by deploying the convenience sampling technique. Prior to this a pilot study consisting of 25 people was conducted to evaluate the reliability of the questionnaire. Furthermore, the questions were examined by textile industry experts, a university professor and an experienced researcher. The suggestions and feedback were incorporated to enhance the understanding of this research instrument. After a period of two months, 410 responses were received, and the elimination of unusable or unfilled questionnaires was carried out and response rate of 40% was noted.

Conflict of Interest

The authors showed no conflict of interest.

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