International Journal of Accounting and Management Sciences
Vol.3 No.4, October 2024
Print ISSN: 2834-8923 Online ISSN: 2832-8175
DOI: https://doi.org/10.56830/IJNZ1133

The Impact of Digital Twins on Accounting:

Evidence from the Egyptian Environment

https://www. doi.org/10.56830/IJAMS10202402

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Received: 7 September 2024. Accepted: 4 October 2024. Published: 1 November 2024

Abstract

This study explored the impact of Digital Twins (DT) technology on accounting processes (Acc) in the Egyptian context. The researchers conducted a survey of 223 academics and professional accountants on the impact of DT on Acc. Using regression analysis, the study found a significant positive impact of DT on Acc in Egypt. The scarcity of research on the relationship between DT and Acc emphasizes the study's scientific value. Practically, the study contributes to Egypt's Sustainable Development Strategy (SDS), enhances businesses' understanding of the economic and operational benefits and challenges associated with DT, and emphasizes the usefulness of DT to accounting processes. Finally, the study urged Egyptian enterprises to integrate DT into accounting processes, thereby enhancing competitiveness, sustainability, and performance.

Keywords: Digital Twins Technology, Accounting, Sustainable Development Strategy, A field Study, digitalization, Egypt.

1. Introduction:

Accounting is the language of business (Coate & Mitschow, 2018). It is the process of identifying, measuring, and delivering economic information to interested users (i.e., stakeholders), such as managers, creditors, investors, and customers (Kwarbai & Omojoye, 2021). According to Cho (2024); (Citak, Owoc, & Weichbroth, 2021), accounting and accountants play pivotal roles in various industries. Accounting has been the backbone of business organizations since its origin, and has thus played a major role in shaping and supporting global economies (Raporu, 2016). Accountants, conversely, are at the heart of financial management, symbolizing a role-modeling process that is essential to every financial transaction and industrial operation. Accounting, being a dynamic field, facilitates the recording of transactions, particularly in terms of financial disbursements (Abdulhay, 2024; Cho, 2024). Essentially, accounting serves as an intermediary for financial transactions. For instance, financial processes are crucial for financial transactions, involved in pharmaceuticals, fertilizers, pesticides, plastics, and food to technology, education, civil engineering, marketing, and all types of businesses, across a wide range of industries (Cho, 2024; (Jejeniwa, Mhlongo, & Jejeniwa, 2024).

Recently, Information and communication technology (ICT)-based technologies have reshaped the operations of numerous professions, including accounting (Chukwuani & Egiyi, 2020). Digital Twins (DT) is one example of contemporary technological disruptions in the accounting industry (ACCA, 2023). DT is a virtual representation of a physical system (twin) that is constantly updated with the same data as the physical system's performance, maintenance, and health status throughout its lifetime (Fuller, Fan, Day, & Barlow, 2020); (Madni, Madni, & Lucero, 2019).

(Fülöp, Topor, Ionescu, Cifuentes-Faura, & Măgdaș, 2023) argued that the introduction of digitalization, including DT, into the accounting profession is inevitable since accounting entails multiple repetitive activities. Digitalization enhances the efficiency of accounting tasks and the accuracy of data being processed and published in financial statements and audit reports. In the accounting profession, digitalization offers advantages such as efficient communication of results and information between departments, faster access to documents, and faster data processing (Ionescu-Feleagă, Dragomir, Bunea, Stoica, & Barna, 2022). Accounting process automation can free accountants from time-consuming chores and allow them to focus on higher-value tasks such as consulting (Raporu, 2016). Furthermore, digitalization can improve the accounting by analyzing large amounts of data in a timely manner (Banța, Rîndașu, Tănasie, & Cojocaru, 2022), increasing the efficiency and effectiveness of accounting activities. (Baldwin, Brown, & Trinkle, 2006).

Despite these benefits, the security concerns associated with digitalization, such as cyber-attacks, may result in data leakage, data misuse, and privacy violations, and hence aversion from deploying digitalization (Fülöp, Topor, Ionescu, Cifuentes-Faura, & Măgdaș, 2023). Also, digital tools could help in such processes of setting targets and managing the processes in realizing them with different approaches of management accounting and control (Tkaczyk, Salina, Lyly-Yrjänäinen, & Laine, 2023).

Business firms realize the transformation of accounting, from traditional accounting work or stand-alone accounting software to Digital Twins accounting service products, which greatly improves the efficiency of accounting work (Liu, 2022). DT offers various benefits to accounting processes, the most essential of which is the ability to model accounting processes and undertake scenario analysis (ACCA, 2023); (Tkaczyk, Salina, Lyly-Yrjänäinen, & Laine, 2023) . Additionally, DT facilitates financial planning, autonomous decision-making and bookkeeping processes, real-time transmission and processing of data, real-time cash flow management, and asset management, and green accounting practices (Atagan Çetin & Pamukçu, 2023); (Mukhtar, 2023).

Despite these benefits, there is a dearth of research on how DT affects the accounting profession both globally and domestically. Therefore, this study adds to the literature by providing evidence on the impact of DT on the accounting profession in Egypt, which serves as a fertile ground for technology-related research due to its Sustainable Development Strategy (SDS), which places a strong emphasis on digitalization.

2. Research Problem:

Several factors have impacted the accounting profession in recent years, one of which is technology (Yigitbasioglu, Green, & Cheung, 2023). Accounting evolution can be categorized into five stages based on technical and technological components: traditional manual, mechanized, automated, robotic and Artificial Intelligence (AI)-assisted accounting (Awang, Shuhidan, Taib, Rashid, & Hasan, 2022). Nowadays, accountants use technology to complete their daily tasks more efficiently and effectively (Stancu & Duțescu, 2021).

However, as the accounting profession's technology adoption slowed (Hassan, 2021), the volume of data began to grow exponentially, and the current technologies employed in the profession began to become outmoded in analyzing large volumes of data in a timely manner so that the information produced could continue to yield benefits (Banța, Rîndașu, Tănasie, & Cojocaru, 2022); (Zhang, Xiong, Xie, Fan, & Gu, 2020).

Furthermore, Adding DT to a company's accounting and analytical structure can simplify data processing for value analysis purposes. DT are also capable of autonomous decision-making, coordination with other DT, self-diagnosis, and problem-solving (Dobrolezha, Mikhailin, Bukhov, & Riabchenko, 2023). According to (Tkaczyk, Salina, Lyly-Yrjänäinen, & Laine, 2023), DT can be used to improve transparency and speed of information communication with the real-time transmission data. It can also serve as a basis for setting Key Performance Indicators (KPIs). DT can also play a significant role in enhancing green accounting practices. However, the adoption of DT faced numerous challenges, including data security concerns, high implementation costs, and the need for skilled personnel (Atagan Çetin & Pamukçu, 2023).

Egypt is executing its vision 2030, which is primarily reliant on digital technologies, making Egypt a fertile ground for digitalization-related research. Therefore, this study aims to examine the impact of Digital Twins ($DT\ (x)$) on accounting ($Acc\ (y)$) as perceived by academics and practitioners in Egypt. The study seeks to address the following main research question: "What is the impact of Digital Twins ($\boldsymbol{DT\ x}$) on accounting ($\boldsymbol{Acc\ y}$) in Egypt?"

Responding to the following supporting questions may help addressing the main research question:

- How DT originated, and what are the different classifications, characteristics, and technologies of DT?
- How accounting operations evolved with technological advancements?
- How DT can be utilized in accounting operations?
- What is the impact of DT (x) on Acc (y) in the Egyptian context?

3. Research Objectives:

The purpose of this research is to explore the impact of Digital Twins ($DT\ x$) on accounting ($Acc\ y$) in the Egyptian context. This can be achieved through:

- Investigating the origins, classifications, characteristics, and technologies of DT.
- Identifying the phases through which accounting operations evolved with technological changes.
- Analyzing how DT can be used in accounting processes.
- Examining the impact of DT on DT (x) on Acc (y) in Egypt.

4. Digital Twins (DT):

This section emphasizes Digital Twins ($DT\ x$). It first discusses the concept of DT, then outlines the origins of DT, identifies the classifications of DT, determines the characteristics of DT, describes the enabling technologies of DT, and finally, analyzes the advantages of DT.

4.1. The Concept of Digital Twins (DT):

The definition and connotation of DT have been adequately covered in the literature. At present, the two most widely accepted definitions were given by (Grieves, 2014) and NASA. NASA defined DT for a space vehicle as (Shafto, et al., 2010): "*A Digital Twins is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best* *available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*".

Accordingly, In (Grieves, 2014) published a white paper about DT, according to which the basic DT model consists of three main parts: (a) physical products in real space (b) virtual products in virtual space, as well as (c) the connections of data and information that tie the virtual and real products together (Grieves, 2014) .

(Hochhalter, et al., 2014), on the other hand, defined DT as a life management and certification paradigm that enables high-fidelity modeling of unique aerospace vehicles across the course of their service lives. Models and simulations include the as-built vehicle state, as-experienced loads and conditions, and other vehicle-specific information.

(Schluse, M.; Rossmann, J., 2016) stated that DT are virtual substitutes of real-world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services. Similarly, (Brenner & Hummel, 2017) described DT as an independently created, automatically updated, and instantly accessible digital copy of a real plant, machine, worker, etc. that is accessible everywhere in real time.

Also, (He, Guo, & Zheng, 2018) defined DT as a dynamic digital copy of physical assets, processes, and systems, which comprehensively monitors their whole life cycle. Additionally, According to (Schluse, Priggemeyer, Atorf, & Rossmann, 2018), a DT is a one-to-one virtual replica of a "technical asset" (e.g., machine, component, and part of the environment).

According to (Bruynseels, Santoni de Sio, & Van den Hoven, 2018), DT is a specific engineering paradigm, where individual physical artifacts are paired with digital model that dynamically reflects the status of those artifacts. (Wang, Ye, Gao, Li, & Zhang, 2019) so argued that DT is a paradigm by means of which selected online measurements are dynamically assimilated into the simulation world, with the running simulation model guiding the real world adaptively in reverse.

According to (Grieves, M.; Vickers, J., 2017), DT is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. Also, (Liu, et al., 2019) also defined DT as a virtual object or a set of virtual things defined in the digital virtual space, which has a mapping relationship with real things in the physical space. Similarly, (Madni, Madni, & Lucero, 2019) defined DT as a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle.

(Söderberg, Wärmefjord, Carlson, & Lindkvist, 2017) recognized DT as more powerful computers, quicker optimization algorithms, and a greater quantity of data accessible, can use simulation to control and optimize goods and production systems in real time. J. (Liu, et al., 2019) defined DT as a new technology, accessing to realistic models of the current state of the process and their behaviors in interaction with their environment in the real world. Also, (Wang, Ye, Gao, Li, & Zhang, 2019) (Wang, Ye, Gao, Li, & Zhang, 2019) defined DT as a unique living model of the physical system with the support of enabling technologies, including multi-physics simulation, machine learning, AR/VR, and cloud service, etc. DT can also be described as Building Information Model (BIM) (Kaewunruen & Lian, 2019); (Kaewunruen, S.; Rungskunroch, P.; Welsh, J., 2018). Ultimately, (Xu, Sun, Liu, & Zheng, 2019) defined DT as physical entities with their functions, behaviors, and rules dynamically.

4.2. The Origin of Digital Twins (DT):

Michael Grieves and his work with John Vickers of NASA represent the origins of DT, with Grieves presenting the concept in a lecture on product life-cycle management in 2003 and defining DT as virtual representation of a physical product containing information about said product (Grieves, 2014); (Jones, Snider, Nassehi, Yon, & Hicks, 2020). In a time when Grieves describes virtual product representations as "relatively new and immature" and data collected about physical products as "limited, manually collected, and mostly paper-based", Grieves and Vickers saw a world where a virtual model of a product would provide the basics for product life-cycle management (Jones, Snider, Nassehi, Yon, & Hicks, 2020).

(Grieves, 2014) Expanded this definition by describing the DT as a collection of three components, a physical product, a virtual representation of that product, and the bi-directional data connections that transfer data from the physical world to the virtual world, and transfer information and processes from the virtual world to the physical world. (Grieves, 2014) Described this flow as a sequence between the physical and virtual states (mirroring or twinning); of data from the physical to the virtual, and of information and processes from the virtual to the physical, as shown in

Figure 1. The virtual spaces themselves consisting of any number of sub-spaces that enable specific virtual operations: modelling, testing, optimization, etc.

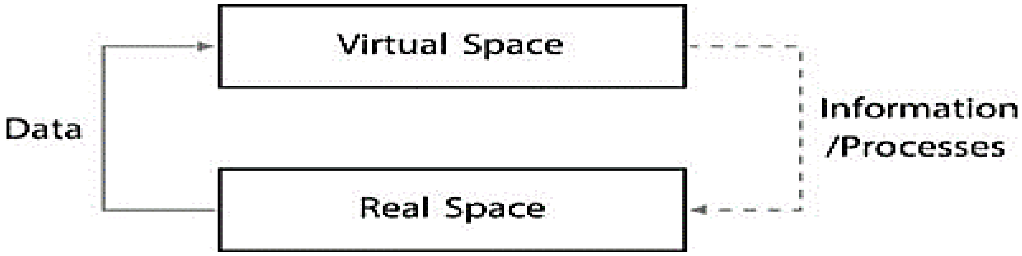

Figure 1: Mirroring or Twinning between the physical and virtual spaces (Jones, Snider, Nassehi, Yon, & Hicks, 2020)

According to (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021), the proposed model has three components: real space, virtual space, and linking mechanism for the flow of data/information between the two; the model was then referred to as “Mirrored Spaces Model” (Grieves, M.; Vickers, J., 2017). A similar concept in which software models mimic reality from information input from the physical world was imagined by (Gelernter, 1993) and was called “Mirror Worlds” (Gelernter, 1993). In (Främling, Holmström, Ala-Risku, & Kärkkäinen, 2003) also proposed “an agent-based architecture where each product item has a corresponding “virtual counterpart” or agent associated with it” as a solution to the inefficiency of transfer of production information via paper for PLM (Främling, Holmström, Ala-Risku, & Kärkkäinen, 2003). By 2006, the name of the conceptual model proposed by Grieves was changed from “Mirrored Spaces Model” to “Information Mirroring Model” (Grieves, 2014); (Grieves, M.; Vickers, J., 2017). As seen in Figure 2, the model focused on the bidirectional connection mechanism between two areas and the creation of several virtual spaces within a single physical space where alternative concepts or designs may be investigated.

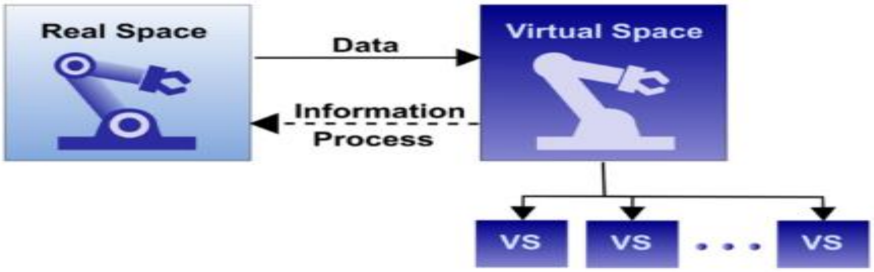

Figure 2: Mirrored Spaces Model (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021)

The name Digital Twins (DT) first appears in NASA’s draft version of the technological roadmap in 2010 (Shafto, et al., 2010). In the NASA roadmaps, DT was also referred to as “Virtual Digital Fleet Leader”. NASA was the first association to forge the definition of DT; it was described as “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin”. The idea was to use DT to simulate the physical and mechanical properties of the aircraft to forecast any fatigue or cracks in the structure, thus prolonging the remaining useful life of the aircraft. (Tuegel, 2012); (Gockel, Tudor, Brandyberry, Penmetsa, & Tuegel, 2012) defined DT only for the aircraft and called it ‘Airframe Digital Twin’ or ADT, which was a computational model to manage the aircraft over its entire lifecycle. Besides monitoring, DT was also proposed for sustainable space exploration as well as for future generations of aerospace vehicles (Glaessgen & Stargel, 2012). The timeline of the evolution of DT can be depicted in Figure 3.

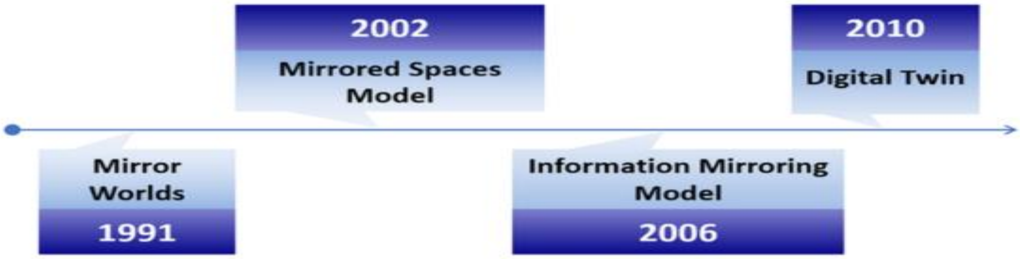

Figure 3: Timeline of evolution of Digital Twins (DT) (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021)

4.3. Classifications of Digital Twins (DT):

Digital Twins (DTs) can be classified into different types based on different criteria, such as when the DT is created, level of integration, its applications, hierarchy, and maturity level. Different researchers have come up with their own nomenclature of DT types based on these criteria. The following is a discussion of DT classifications (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021):

4.3.1. DT Creation Time:

Depending on when in the product life cycle DT is developed, there are two types: before the prototype is made, or during the designing process, or after the product is ready, or during the production phase. On a platform, both kinds of DTs are combined for various purposes and can be called Digital Twins Environment (DTE) (Botín-Sanabria, Mihaita, Peimbert-García, Ramírez-Moreno, Ramírez-Mendoza, & Lozoya-Santos, 2022); (Grieves, 2014); (Grieves, M.; Vickers, J., 2017):

a) Digital Twins Instance (DTI):

DTP can be defined as a digital typeset (DT) that includes all of the data and information needed to produce a physical copy from a virtual version. This include design files, CAD models, BOMs (bill of materials), etc. The cycle of products will begin with the development of DTP, which can undergo several tests, even destructive ones, prior to producing its physical counterpart. Furthermore, DTP assists us in recognizing and steering clear of unforeseen and undesired situations that are hard to pinpoint using conventional prototyping. After DTP is finished and verified, the actual world may produce its physical counterpart.

According to (Botín-Sanabria, Mihaita, Peimbert-García, Ramírez-Moreno, Ramírez-Mendoza, & Lozoya-Santos, 2022), DTI is defined as a kind of DT that, during its entire existence, mirrors its physical counterpart. This means that the physical twin's status is continuously monitored, and whatever changes or development that the physical twin goes undergone will have an effect on the digital twin. In this way, this idea follows a process or product from the beginning to the end, keeping an eye on and forecasting its actions.

b) Digital Twins Prototype (DTP):

After the physical system is constructed, data is transferred from the actual to the virtual domain and back again in order to track and forecast the behavior of the system. These data may be used to determine whether or not the system is exhibiting the anticipated positive behavior and whether or not the anticipated negative possibilities have been effectively ruled out. Any modifications made to one system will also affect the other because of the bidirectional connectivity between them. A collection of DTIs is called Digital Twins Aggregate (DTA) (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021).

According to (Botín-Sanabria, Mihaita, Peimbert-García, Ramírez-Moreno, Ramírez-Mendoza, & Lozoya-Santos, 2022), A DTP collects important data and attributes about the physical twin in relation to product manufacture and production operations. Computer-aided designs (CADs), bills of materials (BOMs), drawings, and even information that might connect the manufacturing process to the parties involved in the production chain are examples of data. The DTP may mimic production scenarios and carry out quality control, validation, and evaluation testing before the real manufacturing process begins, all in line with DT criteria. This method efficiently lowers manufacturing costs and operating time by detecting physical twin defects or potential hazards prior to production. In this regard, DTPs can also be called experiment-able DTs where a virtual prototype becomes available.

4.3.2. Level of Integration:

There are three different integration levels of DT. The integration levels are in ascending order, meaning digital models are the least integrated ones and digital twins are the most integrated (Fuller, Fan, Day, & Barlow, 2020);; (Hribernik, Wuest, & Thoben, 2013):

a) Digital Model:

For the digital model changes must be manually reflected because the virtual and real worlds are not automatically coupled (Fuller, Fan, Day, & Barlow, 2020);. This means once the digital model is created, a change made to the physical object has no impact on the digital model and vice versa. (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021) also claims that in a digital model, the data between the physical and digital object are exchanged manually, due to which any changes in the state of the physical object are not reflected in the digital one directly, and vice versa.

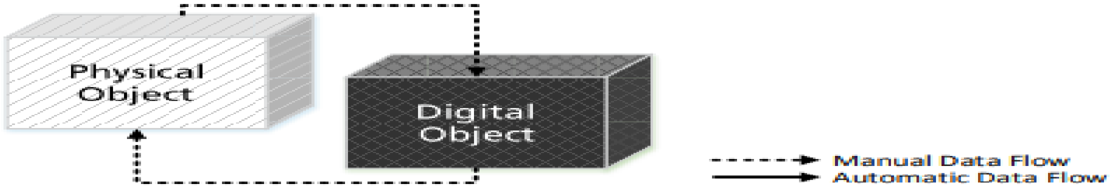

Figure 4: Digital model (Source: (Kritzinger, Karner, Traar, Henjes, & Sihn, 2018)

b) Digital Shadow:

Unidirectional automated information flow from the real world to the virtual world will be integrated via the digital shadow. A system that uses sensors to gather data from the physical model and send signals to the virtual model is the best way to illustrate this. A digital shadow may be used to establish the integration level regardless of whether information is flowed using a polling or interrupt mechanism, provided that it is automated. A digital shadow, as defined by (Fuller, Fan, Day, & Barlow, 2020), is a digital representation of an item when there is a one-way flow between the digital and real objects. It is the digital item that changes when the actual object changes, not the other way around.

According to (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021), in a digital shadow, the data from the physical object flow to the digital automatically, but this is still manual the other way around. As a result, any change in the physical object automatically leads to a change in its digital copy, but not vice versa.

c) Digital Twins (DT):

A fully integrated twin where the virtual and physical world interact in a bidirectional fashion. This implies that data automatically enters and exits each universe. In this instance, data coming from the virtual world will be helpful in modifying the physical model or giving actuators instructions on how to operate. Conversely, information from the physical twin might automatically impact the virtual twin so that it faithfully captures the history and present conditions of its physical counterpart. Also, a change made to the physical object can be seen in its digital object (Fuller, Fan, Day, & Barlow, 2020).

According to (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021), in a DT, ere is an automatic bidirectional flow of data between the physical and digital object. Therefore, the changes in either object, physical or digital, directly lead to changes in the other. **Figure** compares digital models, shadows, and twins.

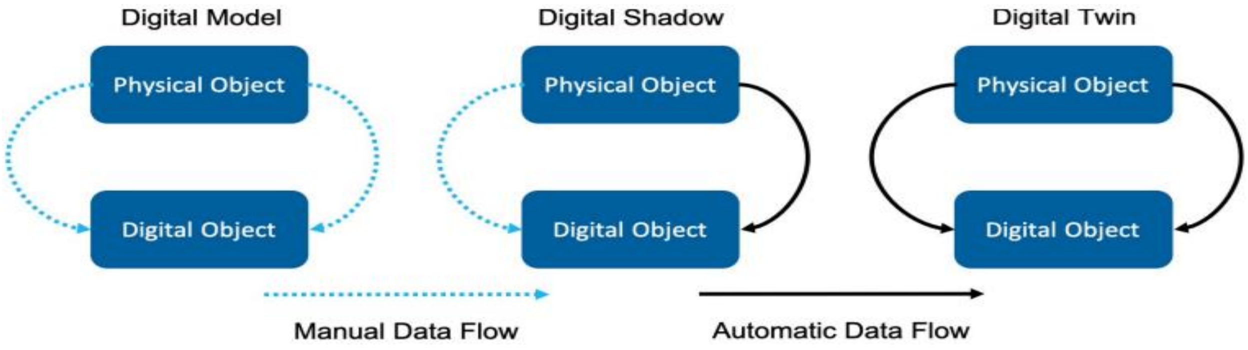

Figure 5: A comparison between Digital model, shadow, and twin (Source: (Fuller, Fan, Day, & Barlow, 2020)

4.3.3. Application:

The two broad applications of a DT are prediction and interrogation (Grieves, M.; Vickers, J., 2017). As the name implies, a predictive DT forecasts the performance and behavior of its physical counterpart in the future, whereas an interrogative DT, regardless of location, is used to question the physical counterpart's past or present conditions. DTs can also be divided depending on if the focus of application is on product, process, or performance (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021):

a) **Product DT:** It is employed in the prototyping process to ensure that the next physical product behaves as intended by analyzing the product under various scenarios. Prototyping can proceed quickly when the product is virtually validated because it reduces the overall development time and eliminates the need to develop multiple iterations.

b) **Production DT:** It is employed to validate processes by simulating and then analyzing them even before the actual production.

c) **Performance DT:** It is used for decision-making processes by capturing, Aggregating, and analyzing data from smart products and plants. In this sense, Performance DT includes performances of both product and production via a feedback loop.

4.3.4. Hierarchy:

DT can be hierarchically divided into three different levels as depicted in Figure , according to the magnitude involved in operations (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021); (Tao, Cheng, Qi, Zhang, Zhang, & Sui, 2018):

a) **Unit level:** It is the smallest unit of participation in the production process and can be a material, a piece of machinery. Unit-level DT is based on the geometric, functional, behavioral, and operational model of unit-level physical twin.

b) **System level:** It is a combination of multiple production system unit-level DTs, including production lines, factory floors, and shop floors. More data flow and more effective resource allocation resulted from various unit-level DT working together and being interconnected. Another example of a complicated product that falls under system-level DT is an aircraft.

c) **System of Systems (SoS) level:** is composed of several system-level DT connected to one another, and facilitates collaboration between various departments or businesses, including supply chain, design, service, and maintenance. Stated differently, SoS-level DT incorporates several stages of the product's life cycle.

The hierarchy of DT can also be classified as: Part/Component twin, Product/Asset twin, System twin, and Process twin, with part twin being the simplest. More sophisticated and comprehensive systems/processes can be achieved by putting together the lower-level twins (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021).

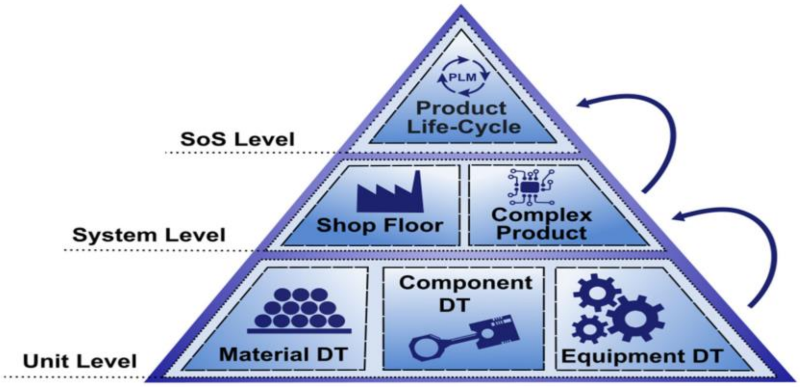

Figure 6: Hierarchical levels of DT (Source: (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021))

4.3.5. Level of Maturity or Sophistication:

Based on the sophisticated level of DT, i.e., the quantity and quality of data obtained from the physical twin and its environment, DTs can be grouped into (Botín-Sanabria, Mihaita, Peimbert-García, Ramírez-Moreno, Ramírez-Mendoza, & Lozoya-Santos, 2022); (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021); Zheng et al., 2019):

a) **Partial DT:** It has a few key data points, such as pressure, temperature, humidity, and so on, that are helpful in figuring out how well DT is connected and operating.

b) **Clone DT:** This includes all important and pertinent information from the system or product that can be utilized to classify development phases and create prototypes.

c) **Augmented DT:** It makes use of the asset's data as well as its history data, extracting and correlating the relevant data with the aid of analytics and algorithms.

The sophistication/maturity level of DT can be improved with the gathering of bigger sets of data over time of operation. On this basis, DT is divided into four levels (Madni, Madni, & Lucero, 2019); (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021) :

a) **Pre-Digital Twin:** DT is created preceding the physical asset for the purpose of making decisions on prototype designs to reduce any technical risk.
b) **Digital Twin:** The virtual system model uses this bidirectional data from the physical asset related to its performance to assist high-level decision-making in the design and development of the asset, along with scheduling maintenance.
c) **Adaptive Digital Twin:** DT at this level has the capability to learn from the preferences and priorities of human operators using supervised machine learning. Using this DT, real-time planning and decision-making during operations is possible.
d) **Intelligent Digital Twin:** This level 4 is more autonomous than level 3 because it has the ability to learn from unsupervised data in addition to the features from level 3. It can identify trends in the working environment, and by combining it with reinforced learning, it makes system analysis more accurate and effective.

4.4. Characteristics of Digital Twins (DT): The common characteristics are (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021); (Tao, Cheng, Qi, Zhang, Zhang, & Sui, 2018).

A. **High-fidelity:** A super-realistic digital model in terms of appearance, contents, functionality, etc. helps DT in imitating every aspect of its physical counterpart. Ultra-high fidelity computer models allow DT simulation and prediction tools to be more reliable.

B. **Dynamic:** The connection and continuous exchange between the physical and DT make the change in DT upon changes on physical system more dynamic and seamless. The data exchanging can be dynamic data, historical static data, as well as descriptive static data.

C. **Self-evolving:** A DT is self-adapting and self-optimizing with the help of the data collected by physical twins in real time, thus maturing along with its physical counterpart throughout its lifetime creating a closed feedback loop.

D. **Identifiable:** Every physical asset needs to have its own DT. During different stages of the product lifecycle, the data and information related to it evolve and so does the model, including 3D geometric models, manufacturing models, usage models, functional models, etc.

E. **Multiscale and Multi-physical:** the virtual model in DT is based on macroscopic geometric properties of the physical twin such as shape, size, tolerance, etc., as well as on microscopic properties such as surface roughness, etc. DT is also based on physical properties of the physical twin such as structural dynamics models, thermodynamic models, stress analysis models, fatigue damage models, and material properties of physical twin such as stiffness, strength, hardness, fatigue strength, etc.

F. **Multidisciplinary:** DT, being the backbone of Industry 4.0, is the combination of fields like automation and industrial engineering, computer science, information technology, and communications; mechanical, electrical, electronic, and mechatronic engineering; and system integration physics.

G. **Hierarchical:** Because each component and portion that makes up the final product has a matching DT model—for example, the DT of an aircraft is made up of rack DT, DT of the flight control system, DT of the propulsion system, etc. As a result, a DT can be thought of as a collection of integrated sub-models.

4.5. Enabling Technologies of Digital Twins (DT):

The key technologies for DT can be grouped into three categories: Data related technologies, High-fidelity modeling technologies, and Model based simulation technologies. Figure shows the technology architecture for DT, which is discussed below in detail (Ala-Laurinaho, 2019); (He, Guo, & Zheng, 2018); (Liu, Fang, Dong, & Xu, 2021):

4.5.1. Data Related Technologies:

Data is the basis of DT. Sensors, gauges, Radio Frequency Identification (RFID) tags and readers, cameras, scanners, etc. should be chosen and integrated to collect total-element data for DT. Industrial IoT (IIoT) and signal processing algorithms in DT can also be used for real-time and multisource data collection. Data then should be transmitted in a real-time or near real-time manner. However, data that DT needed are usually of big volume, high velocity, and great variety, which is difficult and costly to transmit to DT in the cloud server. Therefore, edge computing is a perfect way to pre-process the gathered data in order to lessen the load on the network and avoid the possibility of data leakage, while 5G technology makes it feasible to transmit data in real-time. Understanding the gathered data also requires data fusion and data mapping using for example XML. Application layer protocols, such as HTTP, MQTT, CoAP, XMPP, AMQP, DDS, and OPC UA, and communication technologies, such as 4 G, 5 G, NB-IoT, LoRaWAN, Sigfox, Bluetooth, 802.11 ah, 802.11n, ZigBee, Z-Wave, and WirelessHART, are suitable for sensor data transmission from a physical twin to a DT. They allow easy addition of sensors to a physical twin and provided an interface for their configuration remotely over the Internet (Ala-Laurinaho, 2019).

4.5.2. High-Fidelity Modeling Technologies:

Models of DT comprise semantic data models and physical models. Semantic data models are trained by known inputs and outputs, using AI methods. Physical models require a comprehension of the physical properties and their joint interaction. Thus, multi-physics modeling is essential for high-fidelity modeling of DT such as Modelica. A compromised approach to address the contradiction between simplified virtual model and complex behavior of the physical object is to implement flexible modeling in a modular way by adding black-box modules to the main simulation model. Different behavior models of DT can be activated only when needed. The modules interacted with the main simulation model through standard interfaces.

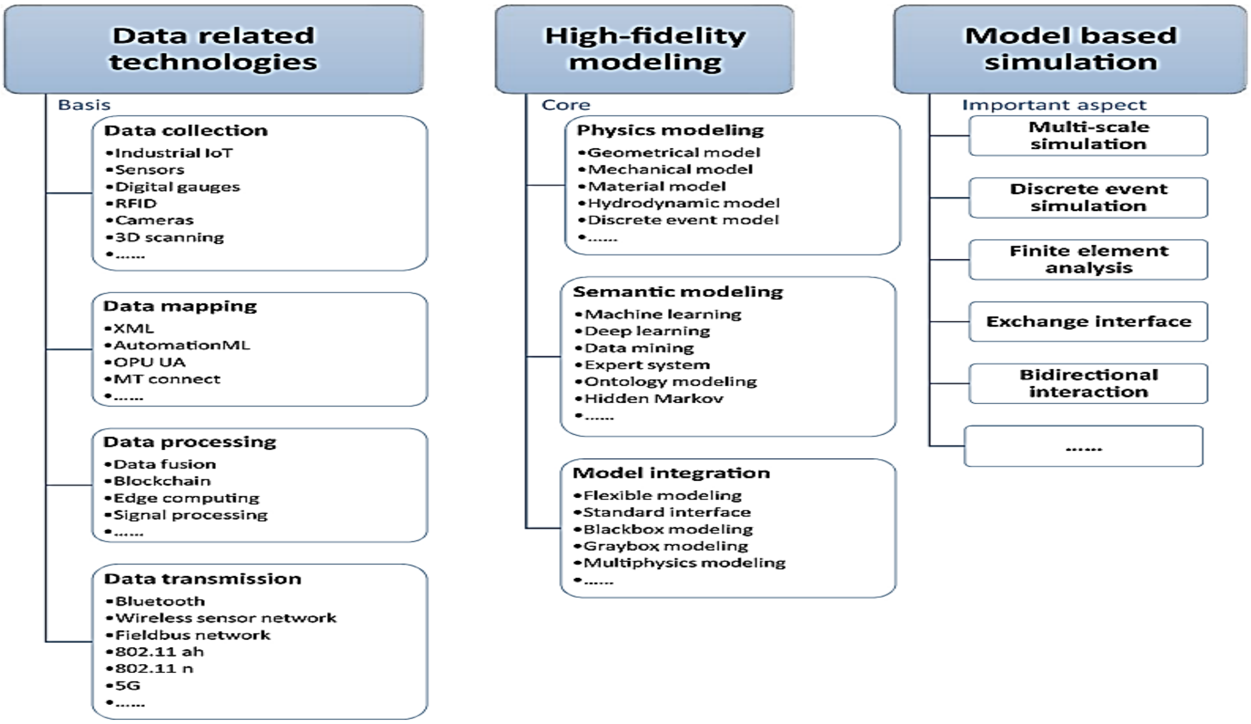

Figure 7: Technology architecture for Digital Twins (DT) (Source: (Liu, Fang, Dong, & Xu, 2021))

For complex manufacturing phenomenon, digital twins can be built using hidden Markov models to summarize the dynamics underlying the phenomenon by using some discrete states and their transition probabilities. Theoretical model, based on Model Based Definition (MBD) techniques, and physical model, built by point cloud scanning, can be fused to commission high precision products' assembly. For complex manufacturing systems, resource virtualization can be a key technology to create DT of a smart factory. Semantic web languages, OWL and Jena are recommended as the modeling languages. DT modeling can usually start with physics-based modeling. Black-box modeling using data or grey-box modeling using a combination of physics and data are also feasible.

4.6. Advantages of Digital Twins (DT)

What make DT the foundation of Industry 4.0 are the key benefits of DT technology, which include a decrease in errors, uncertainties, inefficiencies, and costs in any system or process. A few benefits of DT include (Singh, Fuenmayor, Hinchy, Qiao, Murray, & Devine, 2021); (Tao, Cheng, Qi, Zhang, Zhang, & Sui, 2018) :

4.6.1 Speed Prototyping as well as Product Re-Designing

Prototyping and redesigning are made easier and faster because simulations shorten the design and analysis cycles by allowing the exploration of multiple situations. Once put into practice, DT can be applied at all phases of the product design lifecycle, from ideation to testing. In addition, it opens up the possibility of customizing each product according to the requirements and usage patterns of users. The ability to compare expected and actual performance over the course of the DT's lifetime allows engineers and product designers to reevaluate the presumptions that guided the design of the product.

4.6.2 Cost-Effective

The total cost of prototyping reduces as time progresses because DT is primarily created using virtual resources. DT allows products to be replicated and put through destructive tests without incurring additional material costs. In traditional prototyping, redesigning a product is both costly and time-consuming due to the use of physical materials and labor. Additionally, a destructive test means the end of that expensive prototype. Furthermore, DT makes it possible to test products in a variety of operating conditions, including harmful ones, for free. Once implemented, DT can also lower operational expenses and increase the lifespan of assets and equipment.

4.6.3 Predicting Problems/System Planning

When the complexity of any product increases, it gets harder to predict component failures using conventional methods. However, due to the real-time data flowing between the physical asset and its DT, it can predict problems at different stages of the product lifecycle.

4.6.4 Optimizing Solutions and Improved Maintenance

The traditional maintenance techniques are more reactive than proactive. Nevertheless, DT is able to anticipate flaws and damage in the production apparatus or system, allowing it to plan the product's maintenance ahead of time. Through the process of simulating various scenarios, DT offers the optimal solution or maintenance plan, thereby simplifying the maintenance of the product or system. Furthermore, the continuous feedback loop that exists between DT and its physical equivalent can be utilized to continuously verify and enhance the system's operation.

4.6.5 Accessibility

The physical device can be controlled and monitored remotely using its DT. Unlike physical systems, which are restricted by their geographical location, DT systems can be widely shared and can be remotely accessed.

4.6.6 Safer than the Physical Counterpart

In industries such as oil and gas or mining and in global pandemics where the working conditions are extreme and hazardous, the capability of DT to remotely access its physical twin, as well as its predictive nature, can reduce the risk of accidents and hazardous failures.

4.6.7 Waste Reduction

Prototype designs can be scrutinized virtually, under a variety of different test scenarios, to finalize the final product design prior to manufacture. This not only saves on material wastage but also reduces development costs and time to market.

4.6.8 Documentation and Communication

Data that is dispersed over several software programs, databases, hard copies, etc. must be synchronized in order to form a DT, which makes it easier to access and maintain the data in one location. By improving comprehension of system responses, DT makes it possible to record and convey the behavior and workings of the physical twin.

4.6.9 Training

DT can be used to develop more efficient and illustrative safety training programs than the traditional one.

v4.7 The Impact of Digitalization and Digital Twins (DT) on Accounting

The accounting field is one of the most affected by digital transformation given that most of the tasks performed by accountants are routine ones (Knudsen, 2020); (Stoica & Ionescu-Feleagă, 2021). The digitalization of accounting is associated with disruptive technologies (e.g., Artificial Intelligence (AI), automation of processes by robotics (i.e., Robotic Process Automation (RPA)), blockchain, intelligent data analysis, and cybersecurity) that contribute to reshaping accounting (Coman, et al., 2022).

In accountancy, *DT* could be used to model a company's financial systems, allowing for scenario analysis and improved financial planning. Scenario analysis is the process of forecasting the expected value of a performance indicator, given a time period, occurrence of different situations, and related changes in the values of system parameters under an uncertain environment. Scenario analysis can be used to estimate the behavior of the system in response to an unexpected event and may be utilized to explore the changes in system performance, in a theoretical best-case (optimistic) or worst-case (pessimistic) scenario (Balaman, 2019). For example, a *DT* of a company's supply chain could help accountants understand the financial impact of potential disruptions (ACCA, 2023). According to (Mukhtar, 2023), *DT* can benefit accounting and finance in the following areas:

A. Enhancing Financial Statement Preparation

Using DT technology, accountants can create virtual replicas of financial statement preparation processes. By integrating data from various sources like general ledger, bank statements, and invoices, the Digital Twins model can automate the process. Accountants can simulate different scenarios, test the impact of accounting policies, and optimize financial statement preparation.

B. Tax Compliance and Planning

DT models can be employed to streamline tax compliance and planning activities for businesses. By integrating financial data, tax regulations, and historical tax records, accountants can simulate tax scenarios, evaluate the impact of different tax strategies, and identify potential risks or opportunities. This allows for proactive tax planning, ensuring compliance while maximizing tax benefits.

C. Facilitating Audit Processes

DT technology can revolutionize the audit process by creating virtual replicas of financial transactions, internal controls, and audit trail data. Auditors can leverage these DT models to remotely perform audits, validate compliance, and identify anomalies or irregularities. This streamlines the audit process, reduces costs, and enhances accuracy in identifying potential audit risks.

D. Real-Time Cash Flow Management

It can be utilized to monitor and manage cash flow in real-time. By integrating financial data, invoices, and payment records, accountants can simulate cash flow scenarios, analyze trends, and optimize working capital management. This ensures adequate liquidity and mitigating cash flow challenges.

E. Tax Planning Strategies

DT technology allows accountants to simulate different tax planning strategies and assess their impact on financial outcomes. By incorporating tax laws, deductions, and credits into the DT model, accountants can analyze the tax implications of various scenarios. This enables them to recommend the most advantageous tax strategies to minimize tax liabilities and maximize savings.

F. Automating Bookkeeping Processes

This can automate bookkeeping processes, reducing manual effort and improving accuracy. By integrating Digital Twins models with accounting software and financial data, accountants can simulate bookkeeping activities, validate entries, and automatically reconcile accounts. This streamlines the bookkeeping process, minimizes Errors, and frees up accountants' time for more strategic tasks.

G. Asset Management

Asset management with DT technology can impact financial reporting by providing real-time and accurate data on asset condition and performance. This enables precise asset valuation, proper allocation of maintenance costs, and improved tracking of asset-related expenses throughout the asset life. The insights from DT will assist in decision-making for asset upgrades or replacements, optimizing resource utilization and enhancing financial planning and forecasting. Effective collaboration between accounting and asset management teams is crucial to ensure alignment between financial reporting and the use of DT technology.

A. Bookkeeping

Bookkeeping is the most time-consuming and routine accounting activity, and it is undeniably amenable to automation. Its automation should improve the accuracy of accounting data as well as the time it takes to record it.

B. Fraud Prevention and Detection

Another activity where digital technologies are conceivable, and desirable is fraud prevention and detection. Machines cannot be bribed with money or power because they follow preset rules and act objectively. There are numerous examples of deliberate human decisions and acts that are detrimental to businesses, such as asset theft, tax evasion, cash skimming and larceny, and financial statement fabrication. Thanks to Machine Learning (ML), fraudulent activities can now be predicted and detected.

C. Revenue Forecasting

Despite the availability of models and approaches, forecasting remains a challenging task during periods of uncertainty, information asymmetry, and inherent hazards. Forecasts of revenues must be accurate in order for the operating budget and any budgets that are created from it to function. Machine Learning (ML) algorithms-based predictive models have the potential to improve prediction quality, which in turn can improve budgeting and strategic management procedures. However, accountants need to be especially mindful of the quality of the data collection they use for forecasting and planning since it may have inherent biases. When providing data for the models, they need to use caution.

D. Financial Reporting

Financial reporting is another area that has a lot of room for automation. Some Expert Systems (ESs) were used in the 1980s and 1990s, mostly for cash flow appraisal, business combination analysis, accounting treatment for leases, and financial report analysis for regulatory purposes. In ESs, Financial statements were represented as sets of interconnected cross-sectional equations. However, the growing number of regulations that must be translated into if-then rules and decision trees suited for AI algorithms is a practical challenge.

E. Analysis of Large Amounts of Unstructured Data:

Deep Learning (DL) models can significantly improve the processing of unstructured data such as emails, contracts, graphs, videos, and blogs. Big Data sets may bring new corporate insights, resulting in enhanced decision-making and strategic business solutions. Because of their variety, velocity, and volume, they necessitate specific technology and professional skills relevant to Big Data Analytics (BDA). Accounting professionals are tasked with developing such skills through adequate education and training.

Furthermore, as shown in Table 1, (Petkov, 2020) highlighted prospective accounting tasks that can be delegated to digital technologies, specifically AI. According to (Fülöp, Topor, Ionescu, Cifuentes-Faura, & Măgdaş, 2023), digitalization has immense economic potential. Businesses all around the world are gaining huge benefits from using digitalization into accounting operations, including (Bose, Dey, & Bhattacharjee, 2023); (Petkov, 2020) :

1- Accounting functions employ digital technologies to *provide more accurate and acceptable financial statements*. Because of its proficiency and consistency in analyzing and interpreting accounting data, digitalization can provide information faster than humans. As a result, digitalized accounting functions can produce timely and accurate results. The production of output in real time enhances the timeliness of accounting information and assists users in making informed decisions.

2- Digital technologies, such as an AI that has been well-trained to achieve accuracy, i.e., that has been designed to follow accounting rules, will generate *more accurate and consistent accounting information*. In line with this notion, introducing digitalization into accounting tasks can help to *eliminate accounting and human errors when generating financial statements*. Furthermore, some organizations throughout the world have implemented AI with preset "trained principles," and these companies are reaping the benefits of *increased financial reporting comparability*.

3- Accounting firms are actively integrating digitalization into auditing operations to *assure compliance and eliminate managers' intentional errors*. Managers' ability to employ certain formulants' financial functions would be hampered as a result. Even though just a few accounting firms have integrated digitalization into their auditing functions, the bulk of them utilize digitalization to *manage audit risk*.

4- The most noteworthy advantage of introducing digitalization into a company's accounting function is *the reduction of future costs*. In the long run, relying on digitalization will lessen the need for human operations while improving the efficiency and accuracy of a company's financial reporting (Bose, Dey, & Bhattacharjee, 2023).

According to (Jin, Jin, Qu, Fan, Liu, & Zhang, 2022), digitalization can has many benefits to offer to the accounting profession, including:

1- Digitalization can boost accounting efficiency. Accounting comprises a considerable amount of detailed data that is difficult to manage manually. Digitalization has the potential to automate repetitive accounting duties, simplify complex accounting procedures, and thereby boost accounting efficiency. The digitalization of accounting not only deals with simple data manipulation but also with more complex data analysis and mining tasks, which further increases accounting productivity.

2- Digitalization can improve accounting information quality by augmenting fundamental (such as relevance and faithful representation) and enhancing (such as timeliness) accounting information qualities. Manual accounting procedures introduce accounting errors, lowering the quality of accounting information. Digitalized accounting, on the other hand, uses intelligent accounting software and equipment to objectively process data without the assistance of a human (accountant), thereby eliminating errors and improving accounting information quality.

3- Digitalization can reduce labor costs. Manual accounting required time-consuming and labor-intensive data processing techniques. Accounting and auditing tasks can be completed by robots or intelligent software employing digitalization, decreasing the demand for accountants' time and, as a result, the cost of labor.

4- Using Big Data, AI can analyze structured and unstructured data, boosting the accuracy of data analysis. AI can help businesses obtain a comprehensive grasp of their current business situation and create accurate predictions about future business benefits and risks. AI may be used to produce information from historical data, generalize prior experience, ensure prediction accuracy, and increase the level of intelligence in financial operations.

Concerning the obstacles of utilizing digitalization in accounting, there are certain *fixed costs related to the design, development, and deployment of digital technologies* in a company's accounting function, as well as some *indirect costs associated with monitoring and confirming the performance of digital technologies*. Furthermore, another significant cost of digitalization is its *reliance on the entire system, because if the system is hacked/attacked and no human backup assistance is available, it will become a liability rather than an advantage to the firm*. As a result, proper system maintenance is a vital duty of a corporation prior to using digitalization (Petkov, 2020).

Table 1: A list of manual accounting functions that can be entrusted to AI (Petkov, 2020)

	Human Functions	**Artificial Intelligence (AI) Functions**
Cash	• Manual Input of Cash Receipts and Payments [Use of Journal Entries (hereafter, J/E)]. • Bank Reconciliation performed by individuals reconciling outstanding checks, deposits, errors, interest, etc.	• To scan cash payments/receipts into general ledger (G/L) similarly to how it is done in a Bank Deposit/Withdrawal (regardless of their nature). • To train AI to perform this reconciliation by analysing reconciling inputs and generating bank reconciliation report for reviews by humans.
Accounts Receivable (A/R)	• J/E prepared based on contractual obligation (be it oral or verbal, followed by invoice). • J/E for collection based on receipt of payment. • J/E for allowance for doubtful accounts, based on estimations and assumptions.	• These tasks could be delegated to AI. Specifically, the receipt of cash payments via wire transfers or checks at the point of scanning could result in J/E in the system (similar to Bank Deposits/Withdrawals).
Inventory	• J/E for purchases and sales. • J/E based for lower of cost or market (LCM) value, obsolete inventory, etc. (based on historical data).	• Delegate to AI capable of identifying movement of inventory (ins and outs) and prepare automatic J/Es. • Delegate the estimation of LCM to AI by providing inputs—costs (would come directly from G/L and market, from standard created tool sheet capturing market values of inventory from third parties.
Prepaid	• J/E to record initial asset. • J/E to record period end expense based on use.	• Delegate to AI by training it to scan bank statements and identify such transactions. Humans could continue to be involved to determine duration. Make periodic timely adjustments.
Investments	• J/E for initial recording. • J/E adjustments based on cost or equity method chosen.	• AI to scan bank statement and identify such purchases, record J/Es. • To train AI to analyse F/S of invested companies and seek the activity—such as NI and Dividends and prepare J/Es automatically.
Property, plant, and Equipment (PPE)	• J/E to record PPE purchases; or disposals if any. • J/E for depreciation expense, already done by AI.	• AI to scan bank statements and identify transaction related to PPE purchases and disposals.
Intangibles	• J/E to record intangible purchases; or disposals if any. • J/E for amortization expense, already done by AI. • J/E for goodwill impairment.	• AI to scan bank statements and identify transactions related to intangible purchases and disposals. • Train AI to perform impairment testing by providing key inputs from other departments.
Accounts payable (A/P)	• J/E prepared based on contractual obligation (be it oral or verbal, followed by receipt invoice from vendor). • J/E for payment to vendor.	• These tasks could be delegated to AI. Specifically, the payment of cash payments via wire transfers or checks at the point of scanning could result in J/E in the system (similar to Bank Deposits/Withdrawals).
Accrued Expenses	• J/E prepared based on assumptions and historical data.	• Train AI to analyse such data and make on demand J/Es based on this data.
Unearned Revenue	• J/E to record initial liability. • J/E to recognize revenue based on use.	• Delegate to AI by training to analyse budgets and tie the budgets to actual revenue order and its performance.
Notes payable (N/P)	• J/E to record assumption and repayment of N/P. • J/E for interest payment.	• To teach AI to scan bank statements and identify such transactions. • J/E for interest payment should be based on the contract and therefore could be delegated.
Revenues	• Refer to A/R and Inventory	• Refer to A/R and Inventory
Expenses	• Refer to A/P and Inventory	• Refer to A/P and Inventory

5. The Field Study

In this section, the researchers conduct a field study to examine the impact of Digital Twins ($DT\ (x)$) on accounting ($Acc\ (y)$). The section is divided into two sections: research design and statistical analysis results. The former (research design), establishes the research design followed to address the research question and achieve the research objective, whereas the latter (statistical analysis results) reports the statistical analysis results, including the validity and reliability test, descriptive analysis, correlation analysis, and regression analysis.

5.1 Research Design

This section specifies the research design used to address the research problem. It begins by developing the research hypothesis, then defines the research variables and associated measures, identifies the research population and sampling technique, and, finally, discusses the statistical techniques used in testing the hypothesis.

5.2 Research Hypothesis

After carefully reviewing the literature and examining the theoretical framework, the researchers developed the following research hypothesis:

"$\boldsymbol{H}$: Digital Twins ($\boldsymbol{DT\ x}$) has a significant impact on the accounting process ($\boldsymbol{Acc\ y}$)."

There is a paucity of research on how $DT\ (x)$ affects $Acc\ (y)$ (Tkaczyk, Salina, Lyly-Yrjänäinen, & Laine, 2023). As a result, the researchers developed a two-tailed hypothesis to account for DT's potential positive or negative impact on accounting.

5.3. Research Variables and Associated Measures

This study investigates how Digital Twins ($DT\ x$), the independent variable, affect accounting ($Acc\ y$), the dependent variable. The following is an overview of each variable and how it is measured:

*5.3.1 The Independent Variable (Digital Twins (**DT x**)*

A Digital Twins ($DT\ x$) is the digital representation of a unique asset (product, machine, service, product service system or another intangible asset), that compromises its properties, condition and behavior using models, information and data (Stark, Kind, & Neumeyer, 2017). In this study, the researchers assessed $DT\ (x)$ using a 18-item scale obtained from (Patil, Srivastava, Paul, & Dwivedi, 2024). The items are positively phrased, with higher scores indicating greater DT benefits and readiness for adoption among Egyptian firms, and vice versa. The items are scored on a 5-point Likert scale, with 1 being “Strongly disagree” and 5 being “Strongly agree”.

*5.3.2 The Dependent Variable (Accounting (**Acc y**)*

The art of accounting is known to be dated back over 7000 years ago and have since then evolved from the art of bookkeeping to involve a whole concept concerning communicating financial information about a business (Bygren, 2016). As the ‘‘language of business’’, accounting was first established by Luca Pacioli in 1494. Its main functions are to measure an organization’s economic activities and communicate such information to related stakeholders, such as corporate managers, creditors, consumers, and regulators (Zhang, Xiong, Xie, Fan, & Gu, 2020).

In this study, $Acc\ (y)$ is assessed using a 18-item scale obtained from (Abhishek, et al., 2024). The items are positively phrased, with higher scores indicating higher benefits of DT in accounting operations, and vice versa. The items are scored on a 5-point Likert scale, with 1 being “strongly disagree” and 5 being “strongly agree”.

The questionnaire is, therefore, divided into two sections: section one captures sample characteristics using several demographic variables, such as gender, age, experience, education, and occupation (academic or professional accountant), whereas section two captures respondent perception on the effect of Digital Twins ($DT\ x$) on accounting ($Acc\ y$).

Table 2 summarizes the research variables and associated measures.

Table 2 Research variables and associated scales

Variables	Items	Sources
Digital Twins ($DT\ x$)	18 items (1 – 18)	Obtained from (Patil, Srivastava, Paul, & Dwivedi, 2024)
Accounting ($Acc\ y$)	18 items (19 – 36)	Obtained from (Abhishek, et al., 2024)

5.4. Research Population and Sampling Technique

To capture the perceptions of both academics and practitioners, the research population comprised of academics specialized in accounting, as well as professional accountants in Egypt. Since the population is infinite, and no population frame can be defined, the researchers utilized the non-random Convenience Sampling Technique (CST) in selecting sample participants. Through CST, the researchers can obtain data from individuals who are nearby, readily available, or willing to participate. Accordingly, the researchers used Google Forms to make the questionnaire available to the research population. A total of 223 responses were obtained, none were excluded for invalidity (e.g., missing data), making a sample size of 223 observations.

5.6. Statistical Analysis

The researchers utilized univariate (i.e., simple) regression analysis to test the research hypothesis on the effect of Digital Twins ($DT\ x$) on accounting ($Acc\ y$). The regression model takes the following form:

$$Acc = \beta_0 + \beta_1 DT + e$$

To examine model fit, the researchers use the F test to assess overall model significance, the t test to assess regression coefficient significance, and measures of fit, particularly the coefficient of determination (R^2) and the standard error of the estimate (S_e), to assess goodness of fit. Afterwards, the regression analysis results are used to either support or reject the research hypothesis. Before testing the research hypothesis, the researchers conduct the following tests:

1- Validity and reliability test: Expert opinions (i.e., specialists) and Cronbach's coefficient α are used to assess the measurement scales' validity and reliability.

2- Descriptive analysis: Frequency tables are used to describe sample characteristics based on a set of demographic variables (e.g., gender, age, experience, education, and occupation), whereas measures of central tendency (e.g., the arithmetic mean μ), and dispersion (e.g., the standard deviation σ) are used to describe data on research variables.

3- Correlation analysis: the spearman's rho correlation coefficient is used to analyze the correlation between research variables.

The researchers used the Statistical Package for Social Sciences (SPSS) version 26 in conducting the statistical analysis.

5.7. Statistical Analysis Results

This section presents the statistical analysis results. It begins by examining the validity and reliability of the measurement scales, then describes sample characteristics and variables, analyzes the degree of correlation between research variables, and, ultimately, employs regression analysis to test the research hypothesis on the effect of Digital Twins ($DT\ x$) on accounting ($Acc\ y$) as perceived by academics and professional accountants in Egypt.

5.7.1Validity and Reliability Test

The researchers test the measurement scales' validity using expert opinions and reliability using Cronbach's coefficient α. To examine the validity of the measurement scales, the researchers conducted a set of interviews with experts, both academics and professional accountants. The instrument's readability, comprehension, and coverage of research variables were validated by the experts. Furthermore, the prior use of the measurement scales in the literature strengthens their validity.

Table 3: Reliability analysis using Cronbach's Alpha coefficient

Scale	Items	Cronbach's α	Item Discrimination Index (D)
$DT\ (x)$	18	0.816	0.166 Min – 0.678 Max
$Acc\ (y)$	18	0.858	0.256 Min – 0. 576 Max

The researchers assess the reliability of the measurement scales using Cronbach's coefficient α. A measurement scale with a Cronbach's coefficient α of greater than or equal to 0.7 is deemed reliable. As shown in Table , the α coefficients of the measurement scales exceed 0.7, indicating the reliability of the scales. Furthermore, the Item Discrimination Index (D) shows a moderate to strong correlation between the items on each scale, indicating that the items represent the variables being assessed.

5.7.2. Descriptive Analysis

The researchers use frequency tables to group data on sample characteristics based on a set of demographic variables, including gender, age, experience, education, and occupation. Table shows that out of 223 individuals, 121 (54.3%) were males and 102 (45.7%) were females.

Table 4: Sample Characteristics

Demographic Variables	Total	%
Gender (n = 223)		
Male	121	54.3%
Female	102	45.7%
Age (n = 223)		
Below 30	72	32.3%
From 30 to 50	92	41.3%
Above 50	59	26.5%
Experience (n = 223)		
Below 5 years	76	34.1%
From 5 to 10 years	82	36.8%
Above 10 years	65	29.1%
Education (n = 223)		
Bachelor	81	36.3%
Master	110	49.3%
Ph.D.	32	14.3%
Occupation (n = 223)		
Academics	72	32.3%
Professional accountants	151	67.7%

In terms of age, 72 (32.3%) individuals were below the age of 30, 92 (41.3%) between the ages of 30 and 50, and 59 (26.5%) above the age of 50. There were 76 (34.1%) individuals with less than 5 years of experience, 82 (36.8%) with 5–10 years, and 65 (29.1%) with more than 10 years. In terms of education, there were 81 (36.3%) individuals with a bachelor's degree, 110 (49.3%) with a master's degree, and 32 (14.3%) with Ph. D. Out of the 223 individuals, 72 (32.3%) were academics specialized in accounting and 151 (67.7%) were professional accountants.

Therefore, males made up most sample participants, as did those between the ages of 30 and 50, with 5 – 10 years of experience, with a master's degree, and working as professional accountants.

Table 5: Descriptive analysis

Scale	Mean μ	Standard deviation σ	Min	Max
$DT\ (x)$	3.7394	.59091	1.67	5.00
$Acc\ (y)$	3.6278	.70290	1.50	4.83

The researchers utilized measures of central tendency (the arithmetic mean μ) and measures of dispersion (the standard deviation σ) to describe data on research variables. Table shows the descriptive analysis of research variables.

Digital Twins ($DT\ x$) has a mean score μ of 3.7394, a standard deviation σ of 0.59091, a minimum score of 1.67, and a maximum score of 5.00. This shows that sample participants believe Egyptian firms are well-prepared to realize the numerous benefits of DT. Furthermore, accounting ($Acc\ y$) has a mean score μ of 3.6278, a standard deviation σ of 0.70290, a minimum score of 1.50, and a maximum score of 4.83. This suggests that sample participants believe that applying DT would revolutionize accounting operations.

Correlation Analysis

The researchers use Spearman's rho correlation coefficient to examine the correlation between research variables. As shown in **Table** , Digital Twins ($DT\ x$) is strongly and positively correlated with accounting ($Acc\ y$) (Spearman's rho coefficient = + 0.874). The correlation is also significant (0.000) at α = 0.01.

Table 6 Correlation Analysis

Scale	Coefficient & Significance	$DT\ (x)$	$Acc\ (y)$
$DT\ (x)$	Correlation	1	+ 0.874**
	Significance	---	.000
$Acc\ (y)$	Correlation	+0.874**	1
	Significance	.000	---
**Correlation is significant at the 0.01 level (2-tailed).			

5.7.3. Regression Analysis and Hypothesis Testing:

The section presents the regression analysis and hypothesis testing results. The overall model significance is tested using the F test, the regression coefficient β significance is tested using the t test, and goodness of fit is tested using measures of fit (e.g., the coefficient of determination (R^2) and the standard error of the estimate (S_e)). Based on regression results, the research hypothesis is either supported or rejected. Table summarizes regression analysis results.

Table 7 Regression analysis results

Regression analysis $DT\ (x) \rightarrow Acc\ (y)$		Sig. of coefficients		
		β	t	Sig.
Constant		-0.139	-0.862	0.389
$DT\ (x)$		1.007	23.670	0.000
Overall Significance (F test)	F	560.252		
	Sig.	.000		
Measures of Fit (R^2 and S_e)	R^2	.717		
	S_e	.37469		

The overall regression model is significant at α = 0.01 (F = 560.252, Sig. = 0.000) and the regression coefficient β is significant at α = 0.01 (β = + 1.007, Sig. = 0.000), meaning that the regression model, which uses Digital Twins ($DT\ x$) as an independent variable, adds significant predictability of the dependent variable, accounting ($Acc\ y$), than does a null model that contains only the regression constant. Furthermore, the coefficient of determination (R^2) is estimated at 0.717, meaning that DT (x) explains 71.7% of the variability in Acc (y), and that only 28.3% of the variability in Acc (y) is explained by other variables that are beyond the scope of this study. Also, the standard error of the estimate S_e is relatively low (0.37469), indicating that the regression model fits the data.

The regression coefficient of DT (x) is positive (β = + 1.007) and significant (0.000) at α = 0.01, meaning that Digital Twins ($DT\ x$) has a significant positive impact on accounting ($Acc\ y$). In other words, as DT benefits and Egyptian firms' readiness to adopt DT increase, the benefits of DT in accounting operations increase. Specifically, an increase of one unit in DT (x) increases Acc (y) by 1.007 units. Therefore, the research hypothesis H is supported; Digital Twins ($DT\ x$) has a significant positive impact on accounting processes ($Acc\ y$).

6. Findings and Recommendations

In this section, the researchers summarize the research findings based on the statistical analysis results. Furthermore, the researchers provide several recommendations for Egyptian organizations to enhance their accounting operations using Digital Twins ($DT\ x$) technology. Finally, the researchers present several opportunities for future research.

6.1. Research Findings

Based on the statistical analysis results, the study found that:

1- Males made up most sample participants, as did those between the ages of 30 and 50, with 5 – 10 years of experience, with a master's degree, and working as professional accountants.

2- On average, sample participants believe that Digital Twins (DT) is beneficial to Egyptian firms that are well-prepared for adopting it (μ = 3.7394).

3- On average, sample participants believe that applying DT would revolutionize accounting operations (μ = 3.6278).

4- Digital Twins ($DT\ x$) is strongly and positively correlated with accounting ($Acc\ y$) (Spearman's rho coefficient = + 0.874). The correlation is also significant (0.000) at α = 0.01.

5- Digital Twins ($DT\ x$) has a significant positive impact on accounting operations ($Acc\ y$) (β = + 1.007; sig = 0.000). Therefore, the research hypothesis H is supported.

6.2. Research Recommendations

Based on the statistical analysis results, the study recommends that:

1- Egyptian organizations should be equipped with the appropriate infrastructure to overcome DT's challenges and capitalize its benefits. Furthermore, a cost-benefit analysis is required prior to the adoption of DT.

2- The employees of Egyptian organizations, especially professional accountants and IT specialists should be involved in decisions concerning DT adoption. This would reduce resistance to change and increase technology acceptance.

3- Egyptian organizations should equip their staff with the skills needed to interact with DT. This can be accomplished by hosting workshops and training sessions.

4- Egyptian organizations should regularly review DT performance and challenges. This can assist uncover flaws in DT and take prompt corrective actions.

5- Egyptian organizations should address the privacy and security issues related to the use of DT.

6- Overall, Egyptian organizations should consider adopting DT to enhance accounting operations. This would help enhancing organizations' competitiveness, profitability, and thus sustainability.

6.3. Future Research Opportunities

Based on the findings and recommendations of the study, future research should:

1- Examine the effect of Digital Twins (DT) on Corporate Sustainability.

2- Investigate the relationship between cybersecurity and DT performance.

3- Study the impact of *DT* on green accounting practices.
4- Discuss the impact of *DT* on corporate innovation and control.
5- Analyze the impact of *DT* on firm value and growth.

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Appendix 1: Survey Items

Section I: Sample characteristics
The following questions are designed to capture your individual characteristics. Kindly, take a few minutes to answer the following questions:

1. Gender	☐ **Male**	☐ **Female**	
2. Age	☐ **Below 30**	☐ **From 30 to 50**	☐ **Above 50**
3. Experience	☐ **Below 5**	☐ **From 5 to 10**	☐ **Above 10**
4. Education	☐ **Bachelor**	☐ **Master**	☐ **Ph.D.**
5. Occupation	☐ **Academic**	☐ **Professional accountant**	

Section II: The impact of Digital Twins (*DT x*) on accounting (*Acc y*)

The following questions concern your beliefs about the influence of **Digital Twins (*DT x*)** on **accounting (*Acc y*)**. This instrument is designed to capture the beliefs of both academics and practitioners. Kindly, **take a few minutes to answer the following questions:**	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Digital Twins (*DT x*) (Patil, Srivastava, Paul, & Dwivedi, 2024)					
1. Implementing DT can significantly enhance the efficiency and effectiveness of business operations.	1	2	3	4	5
2. Implementing DT can improve visibility and decision-making.	1	2	3	4	5
3. Implementing DT contributes to cost savings, reduced lead times, and enhanced overall performance.	1	2	3	4	5
4. The advantages gained from DT implementation and integration will outweigh few associated challenges.	1	2	3	4	5
5. Adopting and integrating DT is affordable (time, effort, and finances).	1	2	3	4	5
6. Implementing DT in Egyptian firms requires a clear strategic vision.	1	2	3	4	5
7. Egyptian firms should provide the necessary resources	1	2	3	4	5

(financial, technology, personnel) to support the successful adoption and implementation of DT.					
8. There should be an effective alignment between the leadership's vision for DT and the overall organizational goals in Egyptian firms.	1	2	3	4	5
9. Organizational leadership in Egyptian firms should actively promote and encourage the exploration and utilization of DT.	1	2	3	4	5
10. The successful implementation of DT requires a well-established data infrastructure.	1	2	3	4	5
11. To facilitate DT readiness, data infrastructure in Egyptian firms should have adequate data storage, processing, and integration capabilities.	1	2	3	4	5
12. The data infrastructure in Egyptian firms should align with the requirements for effectively leveraging DT.	1	2	3	4	5
13. The data infrastructure in Egyptian firms should provide a solid foundation for achieving DT readiness.	1	2	3	4	5
14. Egyptian firms should engage in initiatives aimed at improving and optimizing the data infrastructure, recognizing its influence on DT readiness.					
15. Egyptian firms should be well-prepared and equipped to embrace and utilize DT for enhancing various aspects of its operations.	1	2	3	4	5
16. Egyptian firms should understand, implement, and manage DT to improve processes and decision-making within its boundaries.	1	2	3	4	5
17. Egyptian firms should possess the necessary technical expertise and resources to develop and deploy DT	1	2	3	4	5

effectively.					
18. DT is an essential tool for advancing innovation and competitiveness in any organization.	1	2	3	4	5
Accounting (*Acc y*) (Abhishek, et al., 2024)					
19. DT creates a revolution in the accounting process.	1	2	3	4	5
20. DT in accounting transforms business processes.	1	2	3	4	5
21. DT in accounting helps organizations achieve a competitive edge.	1	2	3	4	5
22. Cost-cutting is possible through the integration of DT in accounting.	1	2	3	4	5
23. DT in accounting minimizes the administrative burden on accountants.	1	2	3	4	5
24. The application of DT is essential for future accounting.	1	2	3	4	5
25. DT enhances the efficiency of the accounting function.	1	2	3	4	5
26. DT need to be applied to smoothen the accounting process.	1	2	3	4	5
27. Integration of DT eases the accounting and finance decision-making process.	1	2	3	4	5
28. The use of DT enhances the transparency of accounting.	1	2	3	4	5
29. DT promotes automation which minimizes manual and clerical tasks and saves time.	1	2	3	4	5
30. DT eliminates manual error to the possible extent.	1	2	3	4	5
31. DT in accounting promotes a paperless accounting process.	1	2	3	4	5
32. DT enables real-time reporting.	1	2	3	4	5
33. DT of accounting promotes timely and accurate dissemination of data to end-users.	1	2	3	4	5
34. DT in accounting enables scenario analysis to predict future outcomes at minimal or no cost.	1	2	3	4	5

35. DT in accounting improves financial planning and green accounting practices.	1	2	3	4	5
36. DT in accounting eases asset management and cash-flow management.					