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AMS 100-61

Economics of Digital Twins

Costs, Benefits, and Economic Decision Making

Douglas Thomas

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Abstract

This report examines the economics of digital twins (i.e., digital computer model of a physical system such as a machine or building that has high accuracy, precision, and flexibility to model various aspects of the system) in the manufacturing industry, including the costs, benefits, and economic decision to invest in the adoption of a digital twin. It characterizes the costs and benefits along with the circumstances under which digital twins are likely to be cost effective. Finally, it estimates the potential impact of digital twins to be $37.9 billion annually if they are fully adopted across the manufacturing industry. A Monte Carlo simulation varying key factors of this estimate by -50 % and +20 % (i.e., biasing it downwards) and assuming that digital twins account for between the 80th and 95th percentile of data tracking and analytics investments by cost, puts the 90 % confidence interval between $16.1 billion and $38.6 billion with a median of $27.2 billion annually. From these estimates, one could reasonably surmise that the potential impact of digital twins is likely in the low tens of billions of dollars.

Keywords

Digital Twin; Manufacturing; Investment Analysis; Manufacturing Economics; Modeling; Data Utilization

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Acknowledgments

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Executive Summary

This report examines the economics of digital twins in the manufacturing industry, including the costs, benefits, and economic decision to invest in the adoption of a digital twin. A digital twin is a computer model of a physical system, such as a machine or building, that has the potential for high accuracy, precision, and flexibility to model various aspects of the system. They are used in five primary areas based on the sales of software for implementation (Markets and Markets 2022): predictive maintenance (39.9 %), business optimization (25.3 %), performance monitoring (17.8 %), inventory management (11.9 %), and product design and development (3.4 %). The remaining applications represent 1.6 % of the sales. Three primary factors slow their growth (Markets and Markets 2022): cyber threats, the cost of digital twins, and the required human capital.

Digital twins primarily function to make predictions or as a status indicator for the system being modeled. The benefit of the broader category of data tracking and analytics, which includes digital twins, is being able to identify more optimal design and/or settings for a particular system, such as when to conduct maintenance or where to place machinery. Digital twins provide the potential for high level accuracy, precision, and flexibility in data tracking and analytics, where flexibility is the model's ability to consider different types and levels of input and output factors. The cost effectiveness of investing in a digital twin is likely affected by the complexity and sensitivity (i.e., the level of system variation that affects economic outcomes) of the real-world system being modeled along with the cost consequence of having the non-optimal level of settings or design for the system. A digital twin is more likely to be cost effective for a complex system that has a high-cost consequence for having non-optimal settings/designs; that is, it is cost effective when the costs or losses of having non-optimal settings/design are significant. As system complexity and/or cost consequences of non-optimal settings/designs decrease, digital twins are likely to become less cost effective and models or data tracking with less potential accuracy, precision, and/or flexibility become more cost effective. A "fit for purpose" approach might facilitate more cost-effective digital twin designs. Future research could identify the types of system complexities where digital twins are cost effective along with the situations where an increase in one benefit of digital twins (i.e., accuracy, precision, and/or flexibility) is more beneficial than the others.

The total benefits of all future data tracking and analytics investments in the U.S., including those for digital twins and those with less precision, accuracy, and flexibility, is estimated to be $88.6 billion. If digital twins account for data tracking and analytics investment costs that are above the 85th percentile, the total potential impact of the adoption of digital twins in the manufacturing industry is estimated to be $37.9 billion. Anecdotally, it is common for the highest performing category within a group to account for between the top 10 % and 20 %; thus, the 85th percentile is a significant but reasonable assumption, given the patterns in the costs and return-on-investment found in other similar investments that are discussed in this report. A Monte Carlo simulation varying key factors of this estimate by -50 % and +20 % (i.e., biasing it downwards) and assuming that digital twins account for between the 80th and 95th percentile of data tracking and analytics investments by cost, puts the 90 % confidence interval

between $16.1 billion and $38.6 billion with a median of $27.2 billion annually. These industry level estimates are based on a number of datasets and calculations, including tendencies or patterns in the relationship between the costs and returns on investments entered in the Department of Energy's (DOE) Industrial Assessment Center data. From the industry estimates in this report, one could reasonably surmise that the potential impact of digital twins is likely in the low tens of billions of dollars. Reasonable assumptions are made to calculate the estimates above and these assumptions are relaxed using a Monte Carlo approach. Despite these best efforts, there is a wide range of error in the estimates and the assumptions made are not certainties. Future research could increase the accuracy and precision of these estimates by collecting additional data from manufacturers. Understanding the potential impact affects the investment analysis of public investment in advancing digital twins and their adoption.

In order for the benefits of the broader category of data tracking and analytics investments to be realized, including those from digital twins, the right level of modeling (e.g., digital twin vs. tracking a selection of data items) must be selected based on factors such as the system complexity and cost consequences of having non-optimal system design/settings. If real-world systems are matched with the wrong modeling solutions, the total industry impact will not be realized. Thus, robust methods and practices for investment analysis in digital twins is needed in order for their impact to be achieved. This report briefly discusses investment analysis methods that manufacturers can use for evaluating an investment in a digital twin or other data tracking/analytics solutions.

1. Introduction

Years ago, Dick and Mac McDonald took their staff to a tennis court to rehearse the operations of their restaurant, McDonalds (Murphy 2017). This event, which is depicted in a movie about the McDonald brothers, is a real-life example of successfully using models to gain a competitive advantage. With significant advancements in technology, today a firm can completely model their operations digitally. One model type is a digital twin, which is a digital version of a physical object, system, or process such as machinery, buildings, floor layouts, or a manufacturing process. The average individual might see it as an advanced computer model. Negri (2017) describes digital twins as "representations based on semantic data models that allow running simulations in different disciplines, that support not only a prognostic assessment at design stage (static perspective), but also a continuous update of the virtual representation of the object by a real time synchronization with sensed data. This allows the representation to reflect the current status of the system and to perform real-time optimizations, decision making, and predictive maintenance according to the sensed conditions." Other definitions include the following:

> "A digital twin is a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin" (AIAA Digital Engineering Integration Committee 2020).

> "A digital twin is a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value. The bidirectional interaction between the virtual and the physical is central to the digital twin" (National Academies of Sciences, Engineering, and Medicine 2024).

> "A digital twin is an integrated data-driven virtual representation of real-world entities and processes, with synchronized interaction at a specified frequency and fidelity.
>
> - Digital Twins are motivated by outcomes, driven by use cases, powered by integration, built on data, enhanced by physics, guided by domain knowledge, and implemented in dependable and trustworthy IT/OT/ET systems.
> - Digital Twin Systems transform business by accelerating and automating holistic understanding, continuous improvement, decision-making, and interventions through effective action.
> - Digital Twin Systems are built on integrated and synchronized IT/OT/ET systems, use real-time and historical data to represent the past and present, and simulate predicted futures.

- Digital Twin Prototypes use data to model and simulate predicted futures before being integrated into IT/OT/ET Systems and before synchronization with the real-world entity or process" (Digital Twin Consortium 2024).

Frequently, a major difference between utilizing data or other modeling approaches and a digital twin is the potential level of model accuracy, precision, and flexibility, where

- Model accuracy is the extent to which the model correctly predicts the real-world physical system.
- Model precision is the level of detail that the model accurately predicts the real-world system (e.g., accurate predictions within 1.0 mm vs. accurate predictions within 0.01 mm).
- Model flexibility is the model's ability to consider different scenarios and factors. It includes, but is not limited to, the number of factors that can be changed in the model, the number of factors predicted by the model, and the real-time representation of system being modeled.

In order to achieve more accurate, precise, and flexible system predictions, it often becomes more necessary to employ a digital twin (see Figure 1.1). The threshold for when a model becomes a digital twin is not easily defined; thus, the term is often used to describe what some consider just modeling or data tracking (Wright and Davidson 2020). One might suggest that a digital twin approaches the potential for maximum technologically feasible accuracy, precision, and flexibility in modeling a system.

There are a number of benefits to implementing a digital twin. For instance, it can facilitate more optimal level of maintenance or aid in business optimization. It also can be used for performance monitoring, inventory management, and/or product design and development. Digital twins could even be used for hazard mitigation. Moreover, through the design, manufacture, sale, and usage of a product there are benefits that can reduce costs, accelerate development, increase product quality, and increase utility, as illustrated in Figure 1.2. Digital twins, however, can require significant investments. Although Figure 1.2 shows positive net benefits, this may not be the case for all products and services.

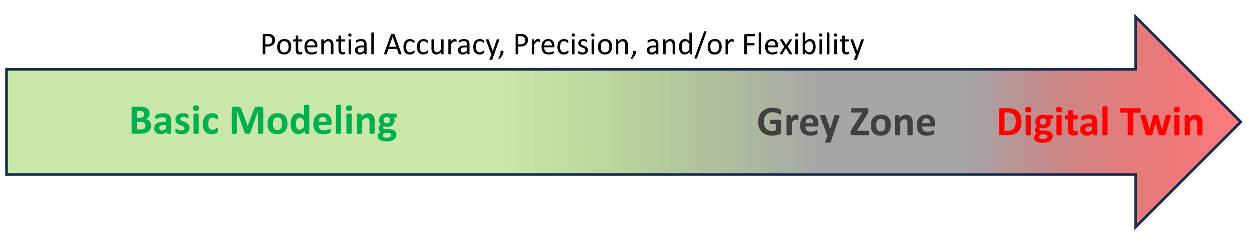


Figure 1.1: Basic Modeling vs. Digital Twin

1.1. Scope

This report aims to examine the economics of digital twins, including methods for investment analysis, costs, benefits, and the circumstances that digital twins are cost effective. The analysis focuses on the manufacturing industry, including the design, production, and inventory of products. It does not examine the application of digital twins by the end user. For instance, it does not examine the impact of an airline using a digital twin for maintenance.

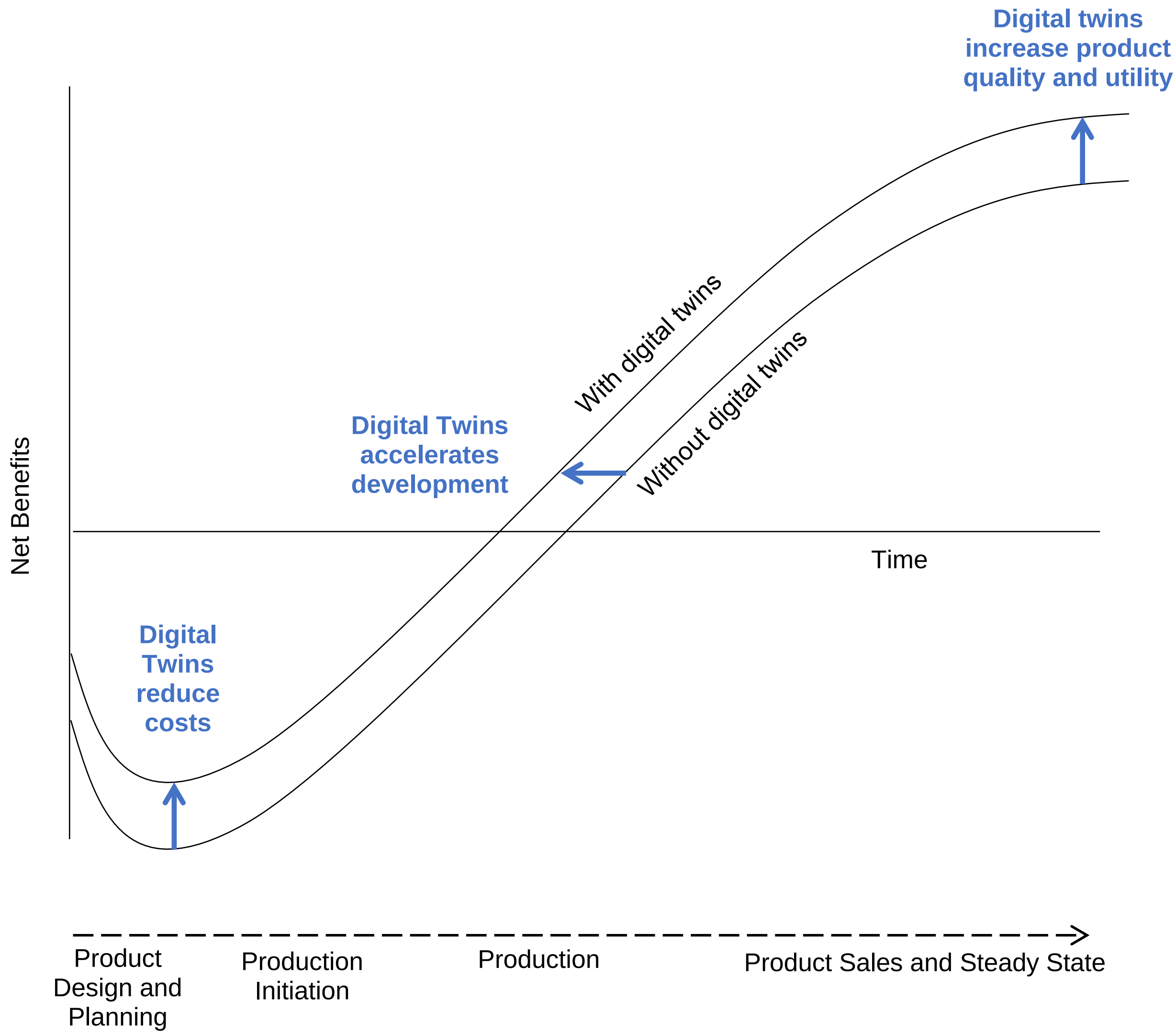


Figure 1.2: Illustration of the Benefits of Digital Twins

1.2. Approach

This report examines data and literature on the economics of using data analysis, modeling, and digital twins in the manufacturing industry. It examines the current application of digital twins such as in predictive maintenance, inventory management, and optimization (Chapter 2). It then discusses the structure of digital twin costs and benefits, including what factors affect the cost effectiveness of them (Chapter 3). Methods for investment analysis of digital twins are discussed and developed in Chapter 4. Chapter 5 uses manufacturing industry data, survey data, and trends in the returns on investments to estimate the potential impacts/savings from data analysis, models, and digital twins. Finally, an estimate of the potential impact of digital twins is estimated.

In practice, there seems to be some disagreement in whether real-time data tracking is required for a model to be considered a digital twin, which would largely exclude modeling for the design of a product. Since many include design activity, this report errs on the side of including those models that do not have real-time tracking, as design activity is commonly referenced regarding digital twins. To reference those digital twins with data tracking, this report uses the term “advanced digital twin.”

2. Current Application and Growth of Digital Twins

As reported by Argolini et al. (2023), in advanced industries an estimated 75 % of companies have adopted digital twins; however, there is significant variation between industries. In the automobile, aerospace, and defense industries, digital twins are more advanced while in logistics, infrastructure, and energy they are in the earlier stages of adoption. There could be many reasons for the differences, which could include the level of competition in an industry, how costs are borne out by different stakeholders, the complexity of a system, and the difference in the costs and benefits of modeling a system using digital twins.

Currently, digital twins are used in a number of applications. The largest application, as measured by sale of products/services to implement it, is predictive maintenance, which accounts for 39.9 % of expenditures (Table 2.1). The products/services measured are software focused, such as those from Microsoft, Siemens, Amazon Web Services, or Dassault Systemes which have been identified as being among the top digital twin providers. It is important to note that there is some variation in the estimate of what is referred to as the digital twin market. For instance, Market and Markets (2022) estimates the global market size at $4.5 billion for 2021 while Global Market Insights estimates the market to be $ 8 billion for 2022. Although the estimates are for different years, it is unlikely that this accounts for all of the difference. The difference in estimates may also be due to data sources and what is considered a digital twin.

Predictive maintenance, the largest application for digital twins, can affect product cost, quality, and production time. The maintenance of machinery typically leads to downtime,

Table 2.1: Percent of Revenue Generated from the Sale of Products/Services to Implement Digital Twins by Industry and Application (Global), 2021

		Industry								
		Automotive and Transportation	Energy and Utilities	Infrastructure	Healthcare	Aerospace	Oil and Gas	Other	TOTAL (%)	TOTAL ($Million)
Application	Predictive Maintenance	7.1%	8.0%	6.4%	7.0%	2.0%	6.4%	3.1%	39.9%	1797
	Business Optimization	4.2%	2.3%	5.4%	2.0%	5.0%	2.3%	4.1%	25.3%	1137
	Performance Monitoring	3.5%	2.7%	0.8%	2.7%	2.5%	1.7%	3.9%	17.8%	801
	Inventory Management	1.6%	2.0%	1.4%	1.6%	2.0%	1.4%	2.0%	11.9%	535
	Product Design and Development	0.4%	0.3%	0.4%	0.3%	1.5%	0.2%	0.4%	3.4%	155
	Other Applications	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.4%	1.6%	74
	TOTAL (%)	17.0%	15.5%	14.5%	13.8%	13.2%	12.2%	13.8%	100.0%	
	TOTAL ($Million)	765	697	653	621	594	548	622		4500
	NORTH AMERICA TOTAL ($Million)	*299*	*262*	*251*	*218*	*230*	*191*	236		*1688*
	US TOTAL									*1383*

Source: Markets and Markets (2022)

either planned or unplanned. Unplanned downtime often stems from breakdowns along with increasing defects when machinery operates outside of specification. This can result in production delays and customer dissatisfaction. The increase in unexpected delays often leads to increased inventory throughout the supply chain to deal with uncertainty, which incurs additional costs.

Generally, there are three primary approaches to manufacturing machinery maintenance. These strategies include the following (which are derived from a series of practical case studies (Jin et al. 2016a; Jin et l. 2016b):

- Predictive maintenance (PdM), which is analogous to condition-based maintenance, is initiated based on predictions of failure made using observed data such as temperature, noise, and vibration.
- Preventive maintenance (PM), which is related to scheduled maintenance and planned maintenance, is scheduled, timed, or based on a cycle.
- Reactive maintenance (RM), which is related to run-to-failure, corrective maintenance, failure-based maintenance, and breakdown maintenance, is maintenance done, typically, after equipment has failed to produce a product within desired quality or production targets, or after the equipment has stopped altogether.

There are limited studies on the costs and benefits of moving between the different maintenance techniques, especially at the aggregated national level. The estimates that have been made, which are mostly at the firm level, show the impacts of PdM are measured using a wide range of metrics and, within each metric, have a wide range of values (Thomas 2018).

Business optimization is the second largest application of digital twins, accounting for 25.3 % of the sale of implementation products/services. It is the largest application for aerospace and the other category while it is the second largest for three other industries. A digital twin allows the simulation of different what-if scenarios in order to optimize machinery, scheduling, and factory operations. It also allows for performance monitoring, which is the third largest application by sales of implementation products/services.

As shown in Table 2.2, there are a number of sources of growth in digital twins, including predictive maintenance and pursuing industry 4.0. However, there are a number of items hindering growth. The largest is the human capital required for collecting data and modeling followed by the high cost of digital twins and the threat of cyber security.

Table 2.2: Approximated Sources of Forecasted Cumulative Growth in Digital Twins, 2022-2027

Source of Growth and Inhibitors	Low	High
Industries reducing cost and advancing supply chains	3%	5%
Healthcare industry	4%	5%
Predictive maintenance	3%	5%
Pursuing real-time data analytics	3%	5%
Pursuing industry 4.0	4%	5%
Using digital twins to examine human health and safety	3%	5%
Threat of cyber attacks	-1%	-2%
High cost of digital twins	-2%	-3%
Human capital required for collecting data and modeling	-3%	-5%
TOTAL	14%	20%

Source: Markets and Markets (2022)

3. Structure of Digital Twin Costs and Benefits

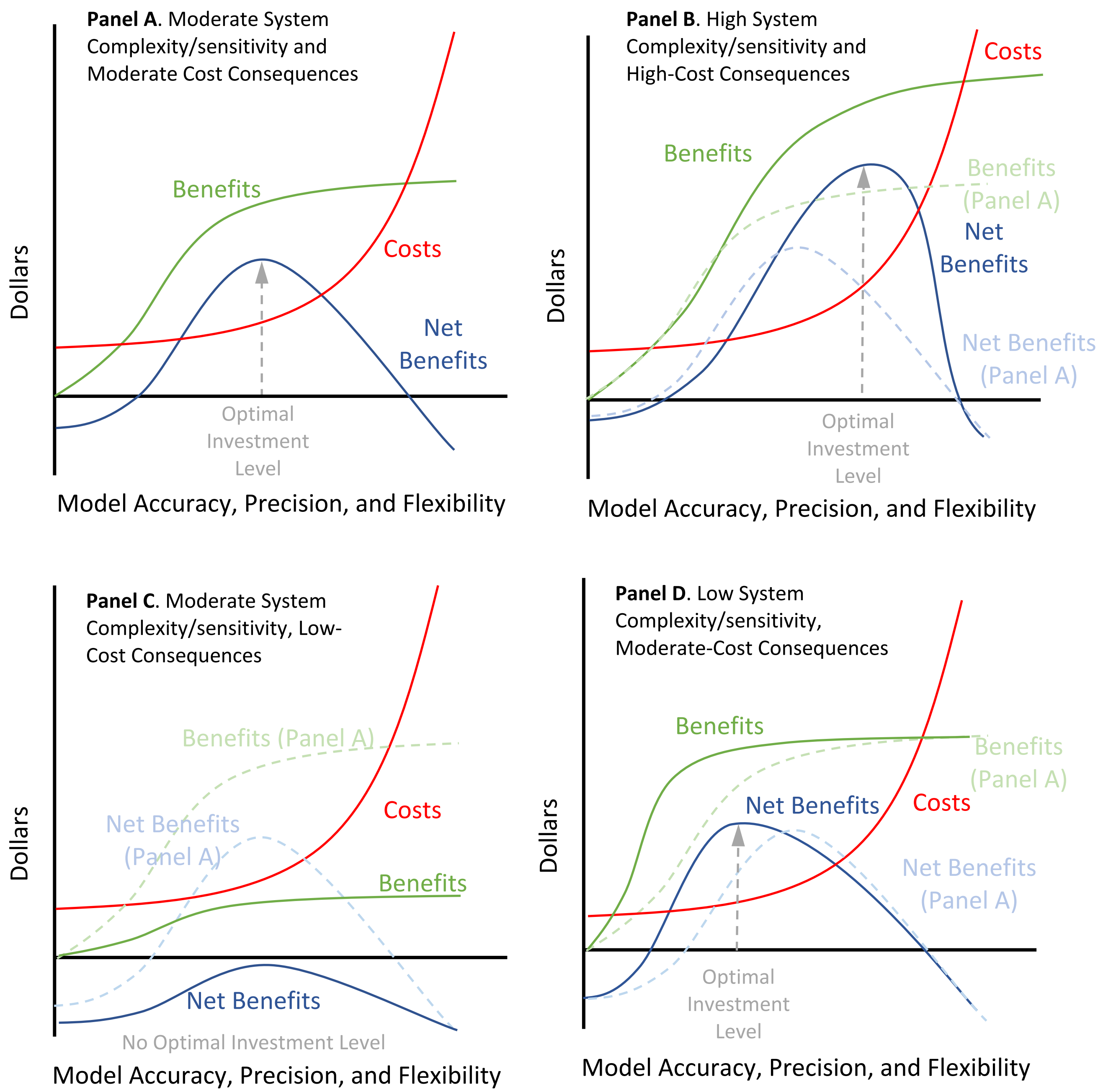
Manufacturing inputs typically follow the law of diminishing marginal returns, which is a theory that states that increasing a single factor of production while holding other factors constant will eventually result in diminishing returns. For instance, consider a factory that has an optimal level of labor when holding all other factors constant. Adding additional labor will eventually result in employees having little work to do and less efficient operations. If one adds enough labor, the people standing around might even get in the way of operations. Similarly, for a particular firm or establishment, there is an optimal level of investment in digital twins where at some point additional investment will result in less efficient operations, when holding other factors constant.

Three primary factors are identified in determining the cost of a digital twin for a particular system. As discussed previously, these factors include the following:

- **Model Accuracy**: The extent to which the model correctly predicts the real-world physical system.
- **Model Precision**: The level of detail that the model accurately predicts the real-world system (e.g., accurate predictions within 1.0 mm vs. accurate predictions within 0.01 mm).
- **Model Flexibility**: The number of factors that can be changed and the number of factors predicted by the model, resulting in the model's flexibility in predicting outcomes from changing different types of factors.

As illustrated in Panel A of Figure 3.1, as a firm increases its model accuracy, precision, and flexibility for digital twins, it would be expected that the benefits increase but eventually they increase at a decreasing rate, which is a typical S-curve as discussed by Kober et al. (2023a). Meanwhile, costs will likely increase at an increasing rate (Kober et al. 2023a). For the illustration in Figure 3.1, the cost function does not change. One might imagine a standardized digital twin that has many options and can be applied to systems with varying complexity, sensitivity, and cost consequences. Item A in Figure 3.1 graphs costs and benefits based on the accuracy, precision, and flexibility of a model, similar to what Kober et al. (2023a) refer to as digital twin fidelity; however, the latter focuses on digital twin solutions while the former allows for non-digital twin solutions. Items A through D in Figure 3.1 demonstrate how the benefits shift from increasing/decreasing system complexity/sensitivity and increasing/decreasing the cost consequences of not having the optimal system options/design, as discussed below.

There are two major factors that are likely to determine the cost effectiveness of investing in a digital twin for a system. The first factor is the **complexity and sensitivity** of the real-world system being modeled. As the number of factors in a system increases, including inputs and outputs, it becomes increasingly more difficult to ascertain the optimal system design, including maintenance and optimal usage parameters. Optimal system parameters may also change over time, making it even more difficult to identify optimal settings and design. System complexity includes, but is not limited to, both the number of factors in a system and the range of options for each factor (e.g., binary options or continuously variable options). The sensitivity of the



Panel A is adapted from Kober et al. 2023a
NOTE: System complexity refers to the complexity of the system being modeled.
NOTE: Cost consequence refers to the cost consequence of having a non-optimal design.
NOTE: For illustration purposes, it is assumed that the function for the costs of modeling is unchanged as the system and cost consequences change.

Figure 3.1: Illustration of Tendencies for Short-Run Net Benefits for Investing in Digital Twins. Panel A through D Illustrate Shifts Due to Changes in System Complexity/Sensitivity and Cost Consequences of Non-optimal System Settings/Design

system refers to the level of variation that affects outcomes from the system. The other major factor for cost effectiveness is the **cost consequence** for each factor and each factor's range of options. Note that cost in this context can include losses, lost revenue, lost opportunities, or other consequences of a non-optimal design or usage.

Benefits of digital twins typically occur as a result of averting losses. For instance, consider a fictional example of two systems: 1) a fighter jet and 2) a Humvee. Also, consider two purposes for these systems: 1) military combat and 2) public relations display. Together, these represent four scenarios:

1. Fighter jet used for combat operations,
2. Humvee used in combat operations,
3. Fighter jet used for public display, and
4. Humvee used for public display.

In this example, the fighter jet is assumed to be a complex system while the Humvee is assumed to be less complex. A disruption in combat operations is assumed to be a high-cost consequence while disruptions in public displays are assumed to be a low-cost consequence. A digital twin is more likely to be cost effective when it is built into a fighter jet that is used for combat, as it might ensure proper operation of the jet and its weapons, increasing the likelihood of mission success. These are the types of benefits that accrue and are graphed in Figure 3.1. A digital twin might not be as cost effective for a fighter jet that is only used for display, such as at an airshow, as the consequence of system failure, and risk to life and property, is far less than in a combat situation. A digital twin would likely be less cost effective for a Humvee that is used for combat than the fighter jet for the same purpose, as the system is not as complex; however, it might still be cost effective in that it ensures performance during critical operations. A digital twin would be even less cost effective for a Humvee that is only used for public display; however, some form of maintenance tracking and sensors would be cost effective, similar to sensors and tracking for oil changes in many modern cars.

If a system has high complexity but the options have little effect on the cost/benefit outcome, then investing in determining the optimal system design may not be cost effective; that is, it may not be cost effective to invest in digital twins. A system that has high complexity and high-cost consequences will likely shift the optimal level of investment up and to the right when compared to those with moderate complexity and cost consequences, as illustrated in Panel B of Figure 3.1. The higher-level complexity requires more complex modeling, accounting for the rightward shift, while the higher cost consequence means higher benefits, accounting for the upward shift. This is similar to the example of the fighter jet being used in combat, as discussed above. Note that Figure 3.1 holds the graph of costs constant to examine the effect of system changes. A system could have a moderate level of complexity and a lower level of cost consequences. This situation is represented by Panel C in Figure 3.1, where the optimal investment level is shifted downward to the point where there is no optimal level of investment, because it is not cost effective. This might be similar to the example of the Humvee being used for public display. The last situation from Figure 3.1 is from Panel D where there is a low level of complexity but a high level of cost consequences. The result is a leftward shift in the optimal level of investment in modeling (i.e., lower model accuracy, precision, and flexibility). This situation might make it cost effective to invest in modeling but not necessarily at the level of modeling that is considered a digital twin. This might be similar to the example of the Humvee being used in combat. It is also important to note that some system types might have a correlation of cost consequences and system complexity. This can be due to, for instance, more and higher cost components.

The tendencies for the effect of more/less complexity and cost consequences on the optimal investment level are summarized in Figure 3.2. As the cost consequences increase for non-optimal design, the benefits increase (vertical arrows) with all other things being equal. As a system becomes more and more complex, it requires more model accuracy, precision, and flexibility to maintain the same level of benefits (horizontal arrows) with all other things being equal. For some instances, costs of modeling exceed benefits at all points; that is, the benefits never exceed the costs. Also, as one moves toward the right side of Figure 3.2, costs will start to exceed benefits. One last item to note is the angled line for system complexity, which illustrates the potential correlation in complexity and cost consequences since complex systems often have higher cost components.

To illustrate the two factors for cost effectiveness, consider developing a digital twin for the maintenance and usage of a stapler. It could have sensors on how the staples move through the

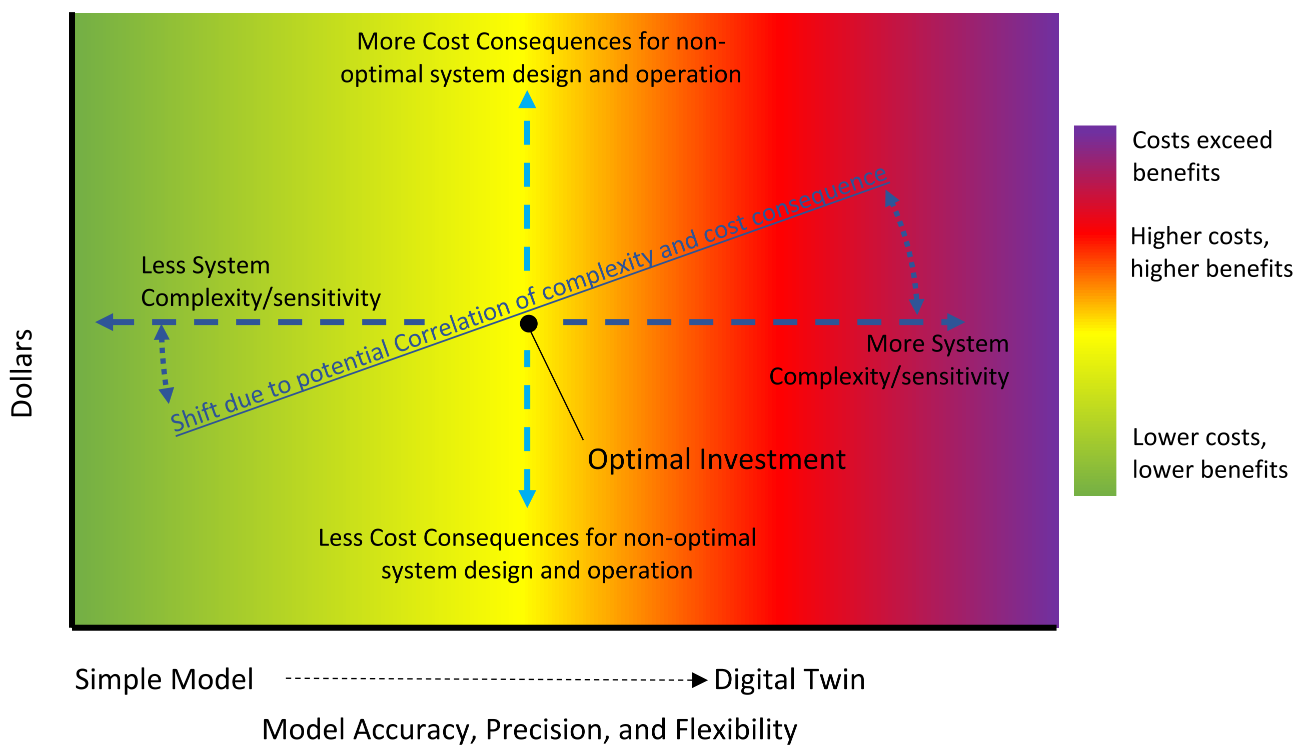


Figure 3.2: Tendency for Optimal Investment, by Shifts in System Complexity and Cost Consequences

stapler, a sensor determining the number of staples remaining before refill, and even a sensor on the pressure applied for each staple so that one can ensure a near perfect stapling experience. However, a stapler is not a complex system, and the consequence of an imperfect staple are so low that the costs of the model, sensors, and tracking likely far outweigh the benefits. This might be similar to Panel C in Figure 3.1, where net benefits never turn positive. On the other hand, consider the assembly of a Boeing 787 Dreamliner. This airplane has millions of parts, making it extremely complex and errors in production can have major consequences, such as when a door plug of a Boeing 737 MAX 9 came off in mid-flight due to a manufacturing error. In this instance, the benefits of a digital twin likely far outweigh the costs. This might be illustrated in Panel B of Figure 3.1, where both the net benefits and level of accuracy/precision/flexibility are high at the optimal investment level.

Another example might be for a small manufacturer with an expensive piece of machinery that requires regular maintenance. This firm might face a situation where there is low system complexity but high-cost consequences. Conducting maintenance too infrequently could result in damage; however, conducting maintenance too frequently results in unnecessary downtime and labor costs. Tracking various factors such as heat and vibration to implement a predictive maintenance program might be the optimal level of investment in modeling. Creating a digital replica of the machine might be costly and yield limited additional benefits. This situation is similar to that of Panel D in Figure 3.1.

A real-life example where a digital twin may not be cost effective might be found in an examination by West and Blackburn (2017). They examine the cost for developing a digital twin for the operation of the Next Generation Air Dominance aircraft for the U.S. Air Force. The paper estimated that the costs of such a model were so high that it was not feasible. Although the digital twin was not cost effective, it is likely that there is a model that has reduced accuracy, precision, and/or flexibility that is cost effective. That is, West and Blackburn (2017) were examining a model so far to the right in Figure 3.2 that it was in the purple zone where costs far exceeded benefits. Moving to the left, they might find a model that is cost effective. This might be akin to or consistent with the concept of a “fit for purpose” digital twin (National Academies of Sciences, Engineering, and Medicine 2024).

Determining the right level of accuracy, precision, and/or flexibility might be complicated. As illustrated in Figure 3.3, increases in accuracy, precision, and flexibility each tends to increase the cost of a model with high levels of all three resulting in a much more costly model. Lower levels of all three might be considered only as modeling while high levels move toward being considered a digital twin with some areas in between being somewhat of a grey area.

One approach for determining the design of a digital twin model might be to determine or estimate the costs and benefits for including each potential input and output or groups of inputs and outputs. Factors where the benefits outweigh the costs would be ranked higher priority for inclusion in the model while those with costs that outweigh benefits would be ranked lower. A prioritization of factors might even be made using net present value or internal rate of return. It is important to note, however, that the interaction of multiple factors may make the inclusion of a group of factors cost effective to include while each individual factor may appear to not be cost effective. The decision maker might use these insights to compare a selection of potential model designs using net present value and internal rate of return combined with an examination of uncertainty using Monte Carlo analysis. Although there is likely a tradeoff between accuracy/precision/flexibility and the ability to control the costs of the model, as illustrated in Figure 3.4, over time it is likely that costs of the model are driven downward where advancements in a firm's experience and expertise reduces the cost of maintaining, using, and possibly expanding the model. This advancement is illustrated by the outward long run integration in Figure 3.4.

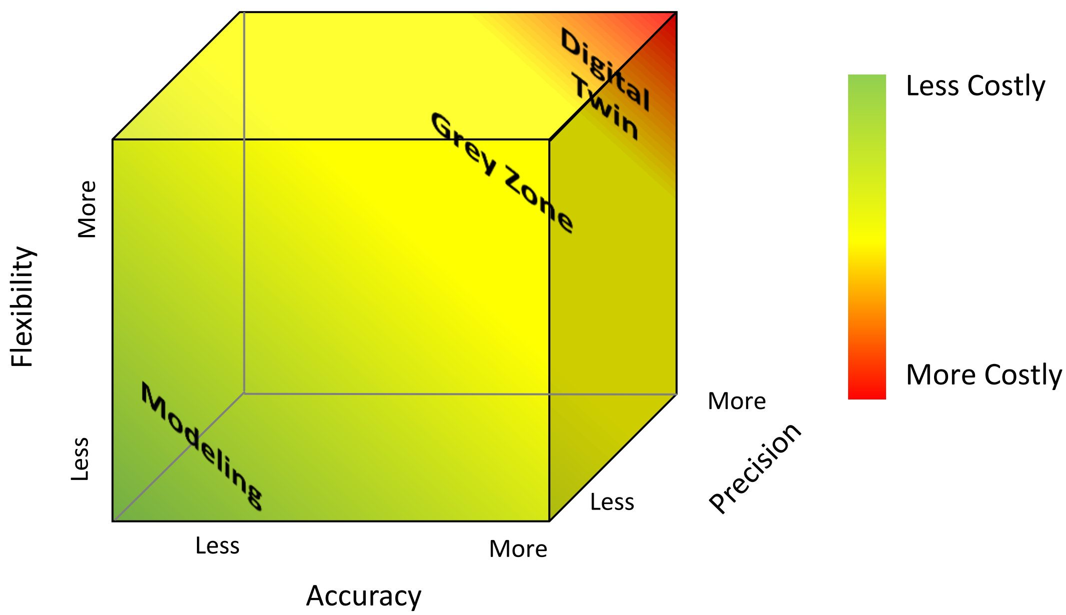
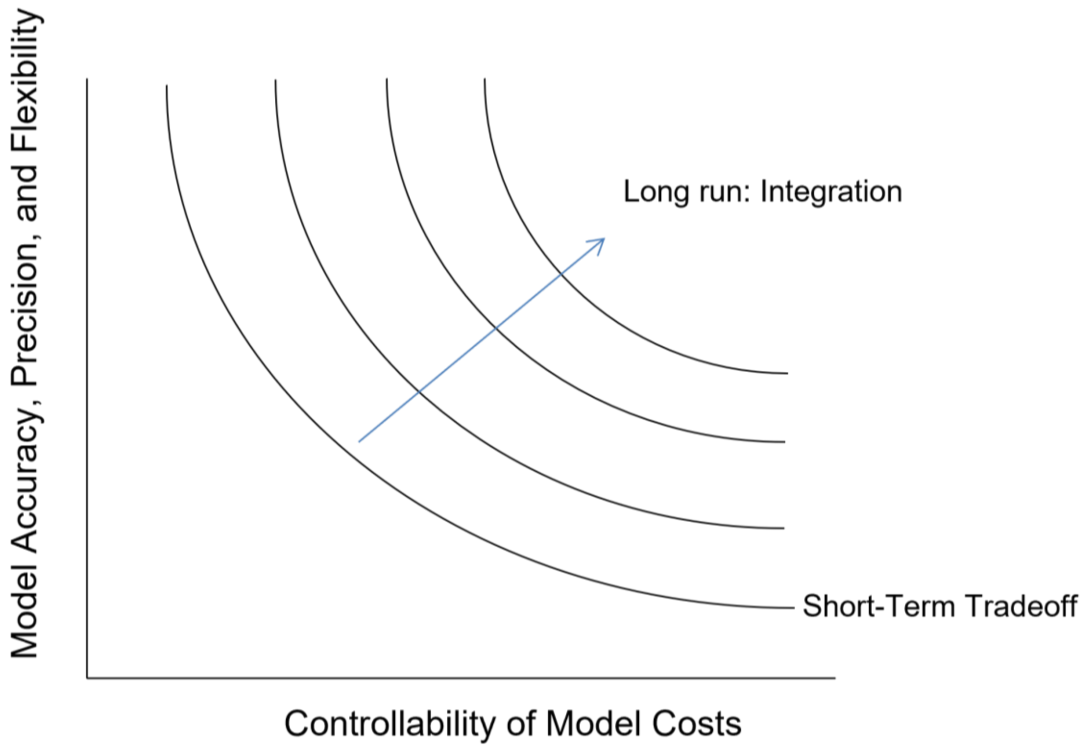


Figure 3.3: Illustration of Digital Twin Investment Costs by Model Precision, Accuracy, and Flexibility



Adapted from Kim and Chulsoon 2013

Figure 3.4: Tradeoff Between Costs and Model Accuracy, Precision, and Flexibility

4. Methods for Investment Analysis

This chapter briefly discusses two methods for investment analysis and sensitivity analysis using Monte Carlo techniques. For a more complete discussion on net present value, internal rate of return, and Monte Carlo analysis, please see Thomas (2017) or other relevant literature cited later in this chapter.

An article by Graham and Harvey (2001 pg 187-243) provides some insight into the usage of net present value and internal rate of return for investment analysis (Graham and Campbell 2001). They surveyed 392 chief financial officers (CFO) about the cost of capital, capital budgeting, and capital structure. Surveys were sent to CFO's for firms listed in the Fortune 500 rankings. Approximately 40 % of the firms were manufacturers and another 15 % were financial. Respondents were asked on a scale from 0 to 4, "how Frequently does your Firm use the Following Techniques when Deciding which Projects or Acquisitions to Pursue." It listed 11 techniques with 0 representing "never use it" and 4 meaning "always use it." The most prominent method used in economic decision making seems to be the internal rate of return. The survey revealed that 75.61 % of respondents always or almost always use this method when making investment decision. The second most common metric was the net present value, where 74.93 % of respondents indicated that always use it or they use it most of the time.

This section relies on widely utilized methods for investment analysis. It is important to note that other alternatives exist that focus on meeting specified objectives. For instance, Kober et al. (2023b) propose a method referred to as the Digital Twin Fidelity Requirements Model (DT-FRM). This model tends to be useful in meeting set criteria in the design of a digital twin but tends not to focus on the possibility of non-digital twin solutions. Another example of a method for prioritizing options might be found in the Analytical Hierarchy Process. Since digital twins tend to be developed for the purpose of reducing costs, this report focuses on investment analysis methods that more directly reflect costs/savings rather than meeting set objectives. It is important to note that different methods can be complimentary or might be better suited for different situations. For instance, the methods below could be used to select among a coarser level of options (e.g., should a firm track data, implement a simple regression model, or develop a digital twin) and the DT-FRM model is used to refine a selected option (e.g., deciding the level of precision for a digital twin).

4.1. Net Present Value

Net present value is the difference between the present value of all cash inflows and the present value of all cash outflows over the period of an investment, where present value is future cash flow discounted to equate its value to cash flows received today (Ross et al. 2005 pg 61; Defusco et al. 2015 pg 2-3, 44-45; Defusco et al. 2001 pg 54-56; Budnick 1988 pg 894-895):

$$NPV = \sum_{t=0}^{T} \frac{(I_t - C_t)}{(1+r)^t}$$

Where:

I_t = Total cash inflow in time period t

C_t = Total cost in time period t

r = Discount rate

t = Time period, which is typically measured in years

T = Study period

Net present value, which accounts for the time value of money, is a common metric for examining an investment, and is considered a superior method over many other approaches (Ross et al. 2005 pg 223; Helfert 2001 pg 235). The net cash inflows for each time period are divided by one plus a selected discount rate raised to the power of the time period, t. The basic interpretation of net present value is that if it is positive, it means that the return on the investment is expected to exceed the discount rate. An anticipated follow-up question is what the rate of return is on the investment. Net present value does not reveal this information. The internal rate of return is more appropriate for answering this question.

4.2. Internal Rate of Return

Internal rate of return is a widely used metric for evaluating investments. It has been suggested that in some industries, it is the principal method used for such analyses. The internal rate of return is, essentially, the discount rate at which the net present value is zero. Thus, it is calculated by setting NPV equal to zero and solving for *r* (Ross et al. 2005 pg 152-153; Defusco et al. 2001 pg 44-49). Due to the nature of this calculation, individuals often use software or trial and error to identify the internal rate of return (i.e., select varying discount rates in order to identify the value where the net present value equals zero).

4.3. Monte Carlo Analysis

To account for uncertainty, a probabilistic sensitivity analysis can be conducted using Monte Carlo methods. This technique is based on works by McKay, Conover, and Beckman (1979 pg 239-245) and by Harris (1984) that involves a method of model sampling. It can be implemented using various software packages such as the Monte Carlo Tool (Thomas 2019b) and the Smart Investment Tool (Thomas 2021) provided by NIST. Specification involves defining which variables are to be simulated, the distribution of each of the variables, and the number of iterations performed. The software then randomly samples from the probabilities for each input variable of interest. Three common distributions that are used include triangular, normal, and uniform. To illustrate, consider a situation where a firm has to purchase 100 ball bearings at $10 each; however, the price can vary plus or minus $2. In order to address this situation, one can use a Monte Carlo analysis where the price is varied using a triangular distribution with $12 being the maximum, $8 being the minimum, and $10 being the most likely. Moreover, the anticipated results should have a low value of approximately $800 (i.e., 100 ball bearings at $8 each) and a high value of approximately $1200 (i.e., 100 ball bearings at $12 each). The triangular distribution would make it so the $8 price and $12 price have lower likelihoods.

For a Monte Carlo analysis, one must also select the number of iterations that the simulation will run. Each iteration is similar to rolling a pair of dice, albeit, with the probabilities having been altered. In this case, the dice determine the price of the bearings. The number of iterations is the number of times this simulation is calculated. For this example, ten thousand iterations were selected and a simulation was ran using Oracle's Crystal Ball software. The frequency graph shown in Figure 4.1 shows the number of times each value was created. Since a triangular distribution was selected, the far left and far right values are less likely to be selected while the most likely value is in the middle at approximately $1000 (i.e., 100 bearings at $10 each). The sum of all the bars in the graph is a probability of 1.0 with a total frequency of 10 000. Instead of a triangular distribution, a uniform distribution could have been selected where each value between $8 and $12 has an equal chance of being selected in each iteration. The results from such a distribution are shown in Figure 4.2. The benefit of Monte Carlo analysis is in the situation where there are many variables that can fluctuate (e.g., price of energy, materials, and labor). Instead of having just one price fluctuating, maybe a dozen prices fluctuate.

4.4. Investment Analysis of Digital Twins

Determining whether an investment in a digital twin is cost effective involves examining the costs and benefits of developing a model (i.e., computer model) of the system in question (e.g., automobile plant, airplane, or a piece of machinery) along with other costs such as sensors and communication mechanisms. It is important to note that an investment analysis is, typically, a

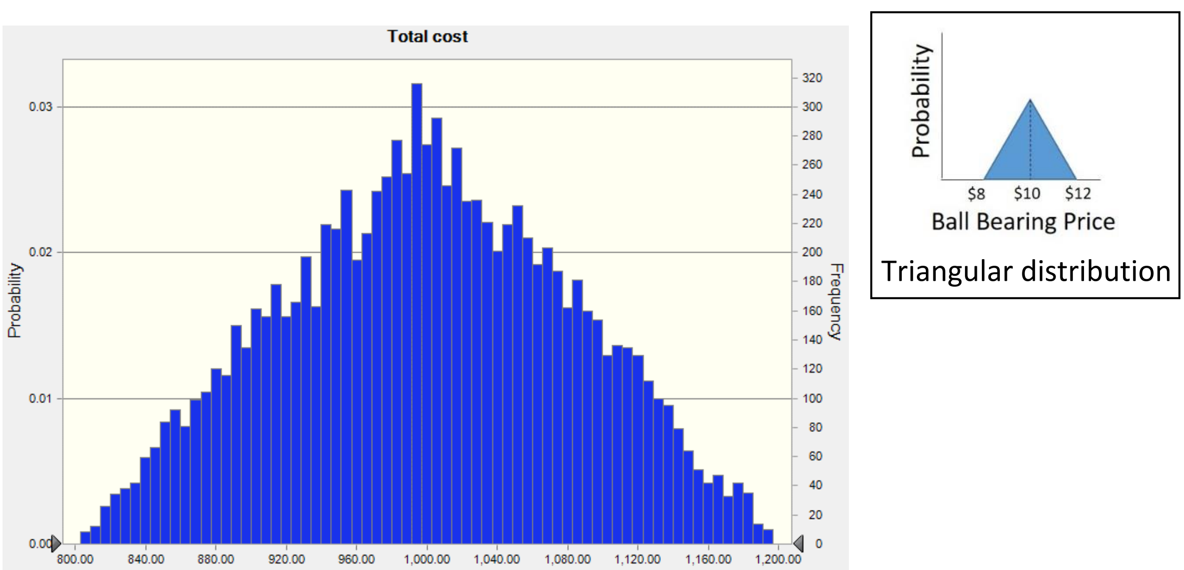
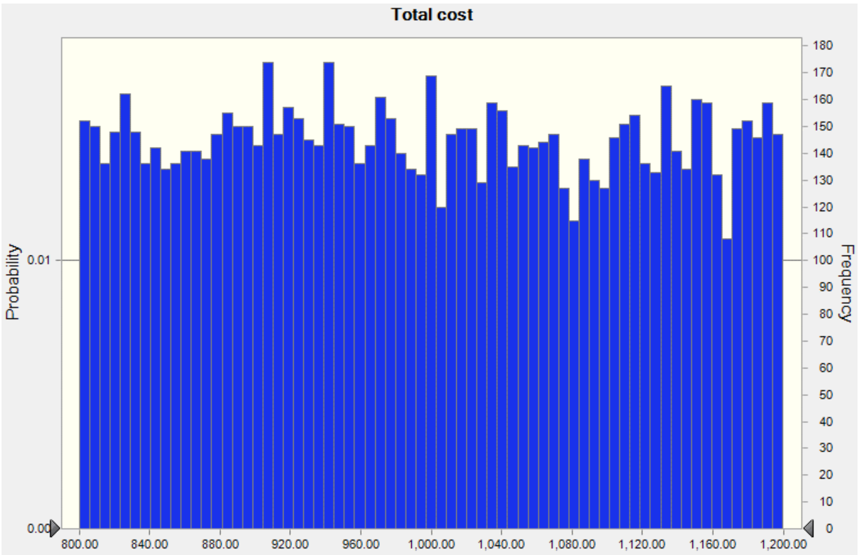


Figure 4.1: Frequency Graph of the Total Cost for Ball Bearing Example using a Triangular Distribution



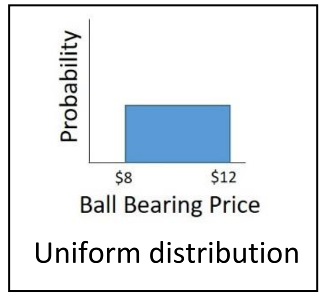


Figure 4.2: Frequency Graph of the Total Cost for Ball Bearing Example using a Uniform Distribution

forecast or prediction of the returns for an investment. Most purchases involve making a prediction or forecast. For instance, the purchase of a toy for a child is typically purchased with the idea that the child will enjoy the toy enough to warrant the purchase; that is, the purchaser predicts that the benefits of the toy will outweigh the costs. Even the purchase of food involves predicting whether the food will be consumed before it spoils and predicting whether it will have a pleasant taste; thus, most individuals have made thousands of forecasts and predictions. Unfortunately, sometimes they are incorrect. We fail to consume food before it spoils, or it doesn't have the pleasant taste that we anticipated. Sometimes children do not enjoy the toys that are purchased for them. Moreover, deciding whether to conduct an investment analysis is not a decision whether to make a forecast or prediction, as that is going to happen whenever an investment/purchase decision is made. Deciding to conduct an investment analysis involves deciding whether one will use standard recognized methods to increase the accuracy and precision of the forecast/prediction. A decision maker will want the most accurate and precise forecast possible; however, there are many unknowns in predicting the future and high levels of accuracy/precision come at a cost.

As mentioned previously, a computer model of a system that has less accuracy, precision, and/or flexibility might be more cost effective than a complex model such as a digital twin, given the costs of developing the model. Therefore, a decision maker needs to consider alternative methods (e.g., simple regression or simply tracking data) for estimating the parameters of the system of concern (e.g., machinery, a manufacturing plant, or a product). These methods may have less complexity than a digital twin, reducing costs while maintaining the same or similar benefits. In addition to considering alternatives, it is also important to consider the options in a digital twin. For instance, one might consider a digital twin of an entire machine or just a digital twin of a single component.

Grouping model options that have common costs (e.g., multiple sensors that feed into a single module) can be useful in identifying cost effective model options. These groupings can be ranked and a selection of model/option designs (e.g., three to five model designs) might be developed and compared. Some example costs to consider might include the following:

- Upfront investment cost to develop a model
- Cost of investing in data tracking (e.g., sensors)
- Cost of analysis
- Cost of maintaining data tracking systems (e.g., sensors)
- Cost of maintaining the model

The costs need to be contrasted with the benefits to having increased accuracy, precision, and model flexibility, such as the following:

- Reduction in flow time and associated costs (i.e., reduced capital and labor per unit of production)
- Reduction in inventory time
- Reduction in defects
- Potential increase in sales due to quality or timeliness

The net present value and internal rate of return for each possible solution or set of solutions might be considered to determine more specifically the optimal level of investment. The net present value for investing in a model or digital twin of a real-world system (versus not investing) might be defined as the following:

$$NPV(DT) = \sum_{t=0}^{T} \frac{\sum_{x=1}^{X}\left(SC_{high-apf,x,t} - SC_{low-apf,x,t}\right) - \sum_{y=1}^{Y}\left(DCA_{y,t}\right) - D_t - MU_t - OTH_t}{(1+r)^t}$$

where

$NPV(DT)$ = Net present value of implementing a digital twin

$SC_{high-apf,x,t}$ = System cash inflows less outflows for cost consequence x at time t in the presence of a system forecast with increased accuracy, precision, and flexibility (high-apf)

$SC_{low-apf,x,t}$ = System cash inflows less outflows for cost consequence x at time t in the absence of a system forecast with increased accuracy, precision, and flexibility.

Cost Consequence = A set or grouping of cash inflows and/or outflows connected to a set of model parameters. For instance, minimizing the motion of a robotic arm requires tracking movement in x, y, and z planes (i.e., model parameters) which is connected to energy and maintenance costs (i.e., set of cash inflows and/or outflows) for the robot.

$DCA_{y,t}$ = Data collection and analysis costs for model parameters y at time t

System = The process(es) and/or physical object(s) being modeled

D_t = Model development costs at time t

MU_t = The costs of maintaining and using the model at time t

OTH_t = Other modeling and implementation costs at time t not defined elsewhere

T = Study period

X = Total number of cost consequences

Note that the benefit that is estimated is the result of being closer to the optimal design or settings while the costs are those to implement the model that provides that information. Note that the net present value discussed in Section 4.1 is the same as the one present here, but with more detail on the types of cash inflows and outflows. As the cash inflows and outflows are specified in more detail, the equation becomes more complex. As discussed below, the investment analysis also becomes more complex as we consider different options for a digital twin.

To estimate the savings or increase in cash flows (i.e., the benefits) of a digital twin, one needs to consider how the benefits are realized. As mentioned previously, there are three categories of benefits for digital twins. A digital twin provides an increase in the potential for (1) precision and/or (2) accuracy in forecasting the outcome of a system design or system settings. Additionally, it might provide forecasts for many different issues, which equates to the (3) flexibility of the model. Each decision maker has a unique situation, but there are three fairly common effects that can be identified for improving precision:

- Continuous or step effects: Although, there may be a limit, for a continuous or step effect each increase in precision tends to increase savings and/or cash flows. An example might be found in modeling a process to increase the yield from a chemical reaction. With each step increase in precision, the system might be changed to result in higher yields, resulting in increased savings and/or cash flows. However, there is some limit to the improvement that can be made for the system.
- Threshold effects: There is a benefit for meeting a threshold; however, after meeting this threshold there are generally no savings or increased cash flows stemming from more precision. For instance, a bolt has to be designed to fit into a nut. Once the bolt is designed such that it fits correctly, there are typically few benefits from increasing the precision of the threads.
- Binary effects: Similar to threshold effects, there is a benefit for achieving a particular design requirement; however, after meeting this goal there are generally no savings or increased cash flows stemming from more precision or accuracy. For instance, a switch is either turned on or turned off.

In conducting an investment analysis of a digital twin, it may be necessary to estimate the savings or cash inflows resulting from these benefits. Threshold and binary effects might be seen as somewhat simpler to estimate. Once the model reaches a certain level of performance, the benefits are realized and there are no more benefits to incorporate thereafter. Continuous or step effects are somewhat more complex. If there are multiple model options for increasing precision for a particular forecast, one might consider estimating and/or graphing the unit increase in precision per dollar of expenditure in order to identify those options with the highest increase in precision per dollar.

In addition to the precision of the forecast, the accuracy is also important. High precision with little accuracy may be of little use for a manufacturer. In determining the value of increasing the accuracy of a forecast, a user would need to consider the consequences of a forecast being incorrect. For instance, one might measure the costs and losses of a predictive maintenance model failing to identify that a machine requires maintenance. Estimating the benefits of increased accuracy is likely to involve probabilities and calculating expected values, as there is typically a probability of a model being accurate or inaccurate.

Discussing every possible scenario is outside of the scope of this report; however, some common issues have been discussed above. As mentioned previously, an investment analysis examining the adoption of a digital twin is itself a forecast. It is a forecast of the costs and benefits of increasing the accuracy of forecasting the performance of a system. Thus, an investment analysis also has some level of accuracy and precision and there are costs associated with increasing them. A Monte Carlo analysis can aid in considering these issues, but the user or manufacturer will need to decide what level of accuracy and precision is acceptable for their investment analysis. Typically, a decision maker would want enough accuracy/precision to determine that an investment has a high probability of being more economical than the next best investment. It is important to note that the benefit of an investment analysis is similar to the benefit of a digital twin, in that it is an increase in the accuracy of a prediction/forecast.

Identifying the more economical choice when there are many options/alternatives that result in many possible scenarios (e.g., 20 possible scenarios) is more complicated than when there are just two scenarios (e.g., one scenario with a digital twin and one without). In the event that there are many options for a digital twin, the selection of options might be made by comparing them using a tiered ranking and selection system where there are options and sub-options. For instance, a model or digital twin of an automobile might have the option of modeling different components within the vehicle. One component might be tracking items in the alternator, which could be considered an option. Within this option, there might be the sub-option to track or place sensors on different parts of the alternator. The IRR might be the better choice for ranking, but NPV could be used as well. The IRR or NPV of each option or sub-option includes only the costs/benefits of including that option and excludes other shared costs/benefits, which are incorporated in the higher-level categories. This process is for simplifying the selection of options.

It is important to note that an investment analysis is typically a forecast and a prediction of the future. Each component of a forecast has some amount of error built into it. Some of the components may have very high error (e.g., guestimate) while others might be small. There is no method of investment analysis with 100 % accuracy; thus, we often use a range of estimates along with sensitivity analysis. Frequently, there are unknown values in an economic assessment; however, there are methods and approaches that can aid in addressing these challenges. In order to conduct a good investment analysis, one needs to utilize the best data, information, and methods available to make the most accurate and precise prediction possible;

however, this will likely never have 100 % accuracy and precision. Recall that typically the goal is to increase accuracy/precision and not to achieve absolute accuracy/precision.

5. Estimated Costs and Benefits of Digital Twins

The previous chapters discussed the application, structure of costs, and methods for conducting an investment analysis of digital twins. This chapter discusses costs and benefits for digital twins with a focus at the industry level. In terms of costs, there tends to be more information relevant to the individual firm or establishment while for benefits/impacts there tends to be more information at the industry level. Section 5.1 discusses estimated costs of digital twins while Section 5.2 discusses the estimated benefits.

5.1. Digital Twin Costs

Implementing a digital twin requires some level of investment with one component being the software for modeling. The average selling price of a digital twin product or solution for one seat is $600 to $800 (Markets and Markets 2022). For instance, the cost from Microsoft is $671 while Robert Bosch is $689 (Markets and Markets 2022). This estimate seems to include only the software necessary. An IT consulting firm estimates that the cost of developing a digital twin application or platform can be $20k to $45k for a small company, $50k to $75k for a midsize company, and $75k to $90k for a large company (RisingMax 2024). Note that these estimates also seem to be for the application and not necessarily for the entirety of the model, sensors, data standardization, and implementation. The programming language, level of complexity, and company size tend to affect the cost (RisingMax 2024). In a survey of 300 C-level executives (i.e., chief executives) in the U.S., which included executives from aerospace, defense, automotive, medical device, oil/gas, and consumer electronics, an estimated 86 % spent $1 million or more annually on digital twins (Dertien and McMahon 2022).

Although this report focuses on manufacturing, there are a number of case studies on applying digital twins to buildings that might provide some insight. For instance, a digital twin for a 600 000 square foot office building has an estimated cost of between $1 million and $2 million for software and hardware with the software accounting for 30 % of the cost (Markets and Markets 2022). Another example of digital twins applied to buildings is a case study of seven building types estimated using public data (Lengthorn 2022). As seen in Table 5.1, the high-tech factory or laboratory building cost between $510 000 and $720 000 and has a 9-year payback period, which is the longest of the seven buildings examined. The shortest payback period is 4 years for a general hospital, which cost between $2.9 million and $4.2 million. The benefits are primarily within operations and maintenance. Each application has its own costs and benefits; thus, it isn’t entirely clear how these estimates apply to manufacturing processes, but it provides some context.

One challenge for implementing a digital twin is acquiring and standardizing the needed data. As discussed by Argolini et al. (2023), implementing a digital twin can be difficult with challenges in compatibility with a company’s current digital practices and environment. This can be one of the barriers for adopting a digital twin. Another cost to consider is the risk of cybercrime, as a digital twin can potentially increase the costs and losses. For instance, a digital twin of a factory could provide competitors with information on how a manufacturer produces their products. Additionally, an outside actor could alter the digital twin, resulting in damages

Table 5.1: Case Study in Cost to Build Digital Twin

Building Type	Square Footage (1000s)	Cost per Sq Ft Low	Cost per Sq Ft High	Total Cost ($1000s) Low	Total Cost ($1000s) High	Payback Period
General Hospital	2 100	1.4	2.0	2 940	4 200	4
High School, Secondary School, Training Center	300	1.0	1.3	300	390	5
Shopping Mall	3 000	1.3	1.9	3 900	5 700	5
University Campus	1 000	1.4	4.9	1 400	4 900	6
Grade A Commercial Office	600	1.9	2.7	1 140	1 620	7
Distribution Center	300	0.9	1.2	270	360	8
High-Tech Factory or Laboratory	300	1.7	2.4	510	720	9

Source: Lengthorn 2022

or losses in production. Losses due to cybercrime are not well understood; however, 2016 cybercrime losses in the U.S. (not specific to digital twins) were estimated by Thomas (2020) to be between $167.9 billion and $770.0 billion or between 0.9 % and 4.1 % of U.S. GDP, a substantial amount of loss that is based on business' estimates of their losses. For manufacturing, the loss is between $8.3 billion and $36.3 billion or 0.4 % and 1.7 % of manufacturing value added. Although, in some applications digital twins might create vulnerability to cyber-attacks, digital twins can also be used to protect manufacturers from attacks by, for instance, simulating cyber-attack scenarios (Balta et al. 2023).

5.2. Digital Twin Benefits

The following subsections discuss the benefits of digital twins, including those from business optimization/performance monitoring (Section 5.2.1), predictive maintenance (Section 5.2.2), inventory management (Section 5.2.3), and product design/development (Section 5.2.4). Some case studies that are discussed have benefits from multiple categories; thus, some subsections may touch on benefits that are the focus of other subsections. Primarily three datasets are utilized for the estimates below, including the Manufacturing Energy Consumption Survey (U.S. Department of Energy 2017), which is referred to as DOE data; Annual Survey of Manufactures (U.S. Census Bureau 2022), which is referred to as ASM data; and NIST's Manufacturing Cost Guide (Thomas 2019a), which is referred to as the MCG data.

5.2.1. Business Optimization and Performance Monitoring

A digital twin can be used to optimize the use and positioning of onsite physical assets and/or physical assets in the supply chain. Some of the benefits of business optimization in manufacturing using digital twins might include the following:

- Onsite benefits

- Reduced machinery motion and movement
    - Decreased flow time resulting in reduced capital per unit of production
    - Reduced energy per unit of production
- Reduced human motion
    - Reduced labor per unit of production
    - Decreased flow time
- Optimize facility layout
    - Reduced capital expenditures on facilities
    - Reduced movement of goods
        - Reduced inventory
- Optimize energy utilization
    - Reduced energy costs

- Supply chain benefits
    - Reduced inventory needed to buffer disruptions and delays
    - Increase in customers due to fewer delays
    - Reduced risk of supply chain disruption

These benefits amount to reductions in flow time, energy for production, production labor, inventory costs, and capital for buildings. Although the total possible savings for manufacturing for each of these is not precisely known, approximations can provide insight such that it reduces error in predicting/estimating possible savings.

The list of benefits above results in six cost savings categories, including cost reductions in the following: onsite material transport, machinery, production labor, energy, production space (e.g., square footage), and work-in-process flow time. To estimate the savings that can be realized from a digital twin or modeling, one can start by estimating the cost savings per 1 % decrease in these six costs.

Onsite Material Transport: Onsite material transport can be approximated by estimating 1 % of the cost for energy, labor, and machinery for onsite transport. Energy is estimated by taking the DOE estimated proportion of Btu's for onsite transport and multiplying it by the ASM's estimate for fuel and electricity costs. The proportion of onsite transport labor calculated from MCG data is used to determine the applicable proportion of machinery; thus, this proportion is multiplied by both the ASM's labor cost (i.e., payroll plus fringe benefits) and an estimate of machinery ($Mach_{Onsite}$), which includes both onsite transport machinery and production machinery:

$$OMT = CR * \left(\frac{OT_{Btu}}{TOT_{Btu}} * (FUEL + ELECT) + \frac{Lab_{Onsite\ Trans}}{Lab_{Total}} (AP + FB + Mach_{Onsite}) \right)$$

where

$$Mach_{Onsite} = \frac{C_{Oth\ Mach}}{C_{Mach}} * (C_{Mach} + C_{Mach\ Rent})$$

and where

OMT = Savings from a 1 % reduction in the cost of onsite material transport

CR = Percent cost reduction (i.e., 1 %)

OT_{Btu} = Total BTUs for onsite transport from DOE

TOT_{Btu} = Total BTUs for all activities from DOE

$FUEL$ = Cost of purchased fuels consumed from ASM

$ELECT$ = Cost of purchased electricity from ASM

AP = Annual payroll

FB = Fringe benefits

$C_{Oth\ Mach}$ = Capital expenditures on "all other machinery and equipment," which includes machinery for production, from ASM

C_{Mach} = Capital expenditures on machinery and equipment from ASM

$C_{Mach\ Rent}$ = Rental and lease payments for machinery and equipment

$Lab_{Onsite\ Trans}$ = Labor costs for onsite transport of materials estimated from the MCG tool. It includes Standard Occupational Classification (SOC) 537011, 537021, 537062, 537063, and 537064.

Lab_{Total} = Labor costs for all manufacturing from the MCG tool.

Machinery for Production: Machinery for production can be estimated by taking the proportion that the "other" category in the ASM data represents and multiplying it by the sum of the capital expenditures on and rental payments for machinery. The machinery in this category, which excludes computers, automobiles, and trucks, that is not used for onsite transport is assumed to be for production. Therefore, the result is multiplied by one minus the ratio for onsite transportation labor. The product is multiplied by the 1 % cost reduction estimate.

$$Mach = CR * Mach_{Onsite} * \left(1 - \frac{Lab_{Onsite\ Trans}}{Lab_{Total}}\right)$$

where

$Mach$ = Cost of machinery for production

Production Labor: Production labor is estimated by taking the proportion of labor costs from the MCG tool and multiplying by the sum of payroll and fringe benefits from the ASM data. The result is multiplied by the 1 % cost reduction.

$$PL = CR * (AP + FB) * \frac{Lab_{Prod}}{Lab_{Total}}$$

where

PL = Savings from a 1 % reduction in the cost of production labor

Lab_{Prod} = Labor costs for production workers and managers, including (Standard Occupation Code) SOC 113051 and 510000

Production Energy: Production energy is estimated by taking the proportion of Btu's estimated for processes from the DOE and multiplying it by the cost of fuels and electricity from the ASM. The result is multiplied by a 1 % cost reduction.

$$PE = CR * \frac{Proc_{Btu}}{TOT_{Btu}} * (Fuel + Elect)$$

where

PE = Cost savings from a 1 % reduction in energy for production

$Proc_{Btu}$ = Total Btu for processes from the DOE

Production Space: The cost of production space is 1 % of the sum of the capital expenditures on buildings, rental payments for buildings, labor for building cleaning/maintenance (BL), building energy use (E_{Bldg}), and purchased building maintenance (PBM) services. It is assumed that on average half of the building space is for production while the other half is for inventory. The ratio of building labor maintenance to total labor from the MCG tool is multiplied by annual payroll and fringe benefits to estimate labor for building cleaning/maintenance. Energy attributed to the building is the ratio of Btu's for HVAC, lighting, and facility support estimated from DOE data multiplied by the costs of fuel and electricity from the ASM. The ratio of labor for building grounds cleaning and maintenance to the total for labor for both machinery and building maintenance is multiplied by purchased maintenance from the ASM to estimate the purchased building maintenance.

$$PS = CR * \left(PBM + 0.5 * \left(C_{Bldg} + C_{Bldg\ Rent} + BL + E_{Bldg}\right)\right)$$

where

$$BL = \frac{Lab_{Bldg}}{Lab_{Total}} * (AP + FB)$$

$$E_{Bldg} = \frac{Bldg_{Btu}}{TOT_{Btu}} * (Fuel + Elect)$$

$$PBM = PM * \frac{Lab_{Bldg}}{Lab_{Bldg} + Lab_{Mach\ Maint}}$$

PS = Cost savings from 1 % reduction in needed production space

Lab_{Bldg} = Cost of labor for building and grounds cleaning and maintenance (SOC 370000) from the MCG tool

$Bldg_{BTU}$ = Sum of Btu for HVAC, lighting, and facility support from DOE.

PM = Purchased repair and maintenance services of buildings and/or machinery

$Lab_{Mach\ Maint}$ = Labor costs for installation, maintenance, and repair (SOC 490000) from the MCG tool

Materials and Packaging: Materials and packaging is the value of materials and packaging from the ASM multiplied by 1 %.

$$MP = CR * MP_{ASM}$$

Where

MP = Materials and packaging saved

MP_{ASM} = Materials and packaging from the Annual Survey of Manufactures

Work-in-Process Flow Time: Savings from reduced work-in-process time is the sum of the production space saved, machinery reduction, and production labor.

$$WIP = PS + Mach + PL$$

where

WIP = Savings from a 1 % reduction in the work-in-process time

Some of the estimates assume ratios of labor costs and those for machinery or buildings are the same. Although this is unlikely to be strictly true, it provides a reasonable estimate. Table 5.2 uses the equations above to estimate a 1 % reduction in each item. Appendix A provides estimates for each of the items listed above. This provides context for potential cost savings both at the firm level, as the percentages provide average industry savings, and the industry level. The largest cost savings is in materials and packaging followed by work-in-process time, which affects multiple cost areas.

The estimates above determine a 1 % change in costs. A multiplier is needed to estimate the reduction in costs from digital twins. Some insight might be gained from case studies and other research. An example of an onsite application is in a case study of an automotive manufacturing plant where a digital twin investment resulted in decreasing the average time to manufacture a car from 14-17 hours down to 9-10 hours, resulting in a 41 %-54 % increase in profits (Miskinis 2018). Machine downtime was reduced by 37 %. Note that if all of automobile manufacturing (NAICS 334) experienced a 41 % to 54 % decrease in work-in-process time, it would equate to a 19.1 % to 25.2 % increase in profits, estimated using the methods from above and data from Table A. 7, which is about half of what this individual facility experienced. Some of the improvements made in the auto manufacturing example would be difficult to achieve without a complex model such as a digital twin. For instance, one improvement was reducing automated machine movement. The change in this instance resulted in reducing a particular movement from 1.235-1.267 seconds down to 0.70 seconds to get from one point to another. Although this seems small, when it is performed thousands of times it adds up. Flow time has a significant impact on the efficiency of production. Every moment that a good is in production or inventory it is consuming resources (e.g., factories, warehouses, and machinery). Flow time can be thought of as water flowing through a hose into a bucket. To meet the demand for water, one can either have multiple hoses flowing at a slow rate or one hose that flows at a fast rate. The slow rate (i.e., long flow time) means more resources (e.g., more hoses) are needed than

Table 5.2: Business Optimization Savings from a 1 % Reduction in Cost

	Among Three Digit NAICS				
	High	Low	Median	Mean	TOTAL
Shipments ($million)	*827 132*	*4 009*	*156 041*	*248 635*	*5 221 325*
Value Added ($million)	*352 469*	*1 840*	*66 577*	*100 354*	*2 107 441*
Profit ($million)	*247 307*	*505*	*33 871*	*49 521*	*1 039 932*
Onsite Material Transport	79.9	0.4	8.6	13.8	289.4
As a Percent of Shipments	0.02%	0.00%	0.01%	0.01%	0.01%
As a Percent of Value Added	0.04%	0.00%	0.02%	0.02%	0.01%
As a Percent of Profit	0.08%	0.01%	0.04%	0.04%	0.03%
Machinery ($millions)	215.8	0.5	41.7	60.2	1 264.5
As a Percent of Shipments	0.04%	0.01%	0.02%	0.02%	0.02%
As a Percent of Value Added	0.17%	0.02%	0.05%	0.06%	0.06%
As a Percent of Profit	0.38%	0.04%	0.12%	0.14%	0.12%
Production Labor ($millions)	579.2	5.7	100.8	166.6	3 498.7
As a Percent of Shipments	0.15%	0.02%	0.08%	0.09%	0.07%
As a Percent of Value Added	0.31%	0.05%	0.22%	0.20%	0.17%
As a Percent of Profit	1.12%	0.06%	0.51%	0.50%	0.34%
Energy for Production	138.2	0.3	17.4	28.2	593.0
As a Percent of Shipments	0.03%	0.00%	0.01%	0.01%	0.01%
As a Percent of Value Added	0.12%	0.01%	0.02%	0.03%	0.03%
As a Percent of Profit	0.27%	0.01%	0.05%	0.07%	0.06%
Production Space	65.2	0.4	11.3	19.8	415.0
As a Percent of Shipments	0.02%	0.00%	0.01%	0.01%	0.01%
As a Percent of Value Added	0.03%	0.01%	0.02%	0.02%	0.02%
As a Percent of Profit	0.10%	0.02%	0.05%	0.05%	0.04%
Materials and Packaging	5 223.0	15.8	580.7	1 236.1	25 957.7
As a Percent of Shipments	0.74%	0.31%	0.44%	0.45%	0.50%
As a Percent of Value Added	5.36%	0.56%	0.97%	1.23%	1.23%
As a Percent of Profit	11.75%	0.74%	2.33%	2.88%	2.50%
WIP Flow Time	777.2	6.6	154.4	245.3	5 151.2
As a Percent of Shipments	0.18%	0.04%	0.12%	0.12%	0.10%
As a Percent of Value Added	0.37%	0.09%	0.31%	0.28%	0.24%
As a Percent of Profit	1.30%	0.12%	0.75%	0.69%	0.50%

NOTE: WIP is the work-in-process flow time.
NOTE: The different savings categories should not be added together, as they overlap.

the fast rate (i.e., short flow time). Thus, if the time is reduced, then the resources consumed are reduced.

Another example of optimization is from a cement factory project in China, which cost almost $136 million and has a production capacity of 4500 tons (Montague 2021). Using a digital twin and a 3D equipment model, operation and maintenance costs were reduced by 30 %. Reduced equipment maintenance costs saved an estimated $2 million while reduced electricity consumption is expected to save $1.24 million. Modeling also reduced construction time by 3 months, saving $3 million and reduced equipment costs by 1.5 % by enabling pre-installation of equipment. Design changes were reduced by 80 %.

5.2.2. Predictive Maintenance

As discussed previously, there are three primary approaches to manufacturing machinery maintenance (Jin et al. 2016a; Jin et l. 2016b). The most advanced is predictive maintenance (PdM), which is analogous to condition-based maintenance, and is initiated based on predictions of failure made using observed data such as temperature, noise, and vibration. The second is preventive maintenance (PM), which is typically scheduled, planned, timed, or based on a cycle. The final maintenance strategy is reactive maintenance, which is often referred to as run-to-failure, corrective maintenance, failure-based maintenance, and breakdown maintenance, and is typically done after equipment has failed to produce a product within desired quality or production targets, or after the equipment has stopped altogether.

There are at least four loss categories due to maintenance issues associated with reactive and preventive maintenance, including unplanned downtime, defects in products, lost sales due to delays or defects, and injuries. Unplanned downtime occurs when machinery unexpected stops working due to a maintenance issue. When this happens it leaves labor and machinery unexpectedly idle. Defects can occur when machinery wears down and moves out of tolerance. Both defects and downtime can result in lost customers. Finally, injuries can occur when machinery breaks down in catastrophic ways.

Digital twins can be used for predictive maintenance to model machinery, predict when maintenance or parts are needed, and plan maintenance rather than reacting to a breakdown. For instance, a costumer of GE Aviation indicated that predictive maintenance improved their time on wing (i.e., operational reliability of an aircraft) by 20 % (Careless 2021). However, predictive maintenance is not cost effective for all situations, rather it is likely more cost effective at higher levels of system complexity and/or higher cost consequences, as discussed previously. For instance, predictive maintenance is not cost effective for a light bulb, as the cost consequence of breakdown (i.e., the bulb burning out) is very low and there is, typically, redundancy in the system where there are multiple lighting sources. It is also important to note that not all predictive maintenance programs use digital twins. Benefits of applying digital twins for predictive maintenance can include, but are not limited to the following:

- Reduced safety risk
- Improved product quality
    - Fewer defects and rework
    - Potential increase in customer base
- Reduced downtime and flowtime
    - Reduced labor per unit
    - Reduced energy per unit
    - Reduced capital per unit
- Reduce costs due to faults and failures (e.g., damaged equipment)
- Reduced delays
    - Potential increase in customers
- Reduced inventory needed to buffer for downtime

The total maintenance costs, losses due to non-optimal maintenance practices, and lost customers is not well understood for all of the U.S. manufacturing industry; however, NIST Advanced Manufacturing Series 100-34 (Thomas and Weiss 2020) examines maintenance costs and losses due to non-optimal maintenance for discrete manufacturing, which includes the following:

- NAICS 321: Wood Product Manufacturing
- NAICS 322: Paper Manufacturing
- NAICS 323: Printing and Related Support Activities
- NAICS 326: Plastics and Rubber Products Manufacturing
- NAICS 327: Nonmetallic Mineral Product Manufacturing
- NAICS 331: Primary Metal Manufacturing
- NAICS 332: Fabricated Metal Product Manufacturing
- NAICS 333: Machinery Manufacturing
- NAICS 334: Computer and Electronic Product Manufacturing
- NAICS 335: Electrical Equipment, Appliance, and Component Manufacturing
- NAICS 336: Transportation Equipment Manufacturing
- NAICS 337: Furniture and Related Product Manufacturing
- NAICS 339: Miscellaneous Manufacturing

The manufacturing industries that are absent or not part of the examination include food manufacturing (NAICS 311), beverage and tobacco products (NAICS 312), textile mills (NAICS 313), textile products (NAICS 314), apparel and leather (NAICS 315 and 316), petroleum products (NAICS 325), and chemical products (NAICS 324). Although not all predictive maintenance programs necessarily utilize digital twins, this study provides some context the extent of benefits that might occur by employing digital twins to maintenance.

2016 Machinery maintenance expenditures for NAICS 321-339 (excluding 324 and 325) were estimated to be $57.3 billion. Additional expenditures due to faults and failures were estimated at $16.3 billion and costs for inventory to buffer against maintenance issues costed $0.9 billion. In total, these maintenance activities costed $74.5 billion, as shown in Table 5.3. To put this in perspective, the 2016 shipments for these industries were $3213.1 billion and the value added was $1503.7, making the sum of these costs to be 2.3 % of shipments and 5.0 % of value added.

Table 5.3: Costs and Losses Associated with Maintenance for Discrete Manufacturing

	Estimate ($2016 Billion)	As a percent of Shipments	As a percent of Value Added	90 % Confidence Interval	
Costs	74.5	2.3%	5.0%	50.8	103.3
Direct Maintenance Costs	57.3	1.8%	3.8%	42.4	72.2
Costs due to Faults and Failures	16.3	0.5%	1.1%	7.1	25.5
Inventory Costs	0.9	0.0%	0.1%	1.3	5.6
Losses	119.1	3.7%	7.9%	43.9	197.3
Unplanned Downtime	18.1	0.6%	1.2%	10.4	27.8
Labor	*13.5*	*0.4%*	*0.9%*	*7.1*	*22.1*
Capital Depreciation Buildings	*2.5*	*0.1%*	*0.2%*	*1.8*	*3.1*
Capital Depreciation Machinery	*1*	*0.0%*	*0.1%*	*0.7*	*1.2*
Energy	*1.1*	*0.0%*	*0.1%*	*0.8*	*1.4*
Defects	0.8	0.0%	0.1%	0	2.7
Lost Sales	100.2	3.1%	6.7%	33.5	166.8
Due to Defects	*31.2*	*1.0%*	*2.1%*	*3.6*	*58.7*
Due to Delays	*69*	*2.1%*	*4.6%*	*29.8*	*108.1*
Total Costs and Losses	193.6	6.0%	12.9%	94.7	300.7

Data Source: Thomas and Weiss 2020

A 1 % savings due to an increase in advanced maintenance (AM) can be estimated by summing the savings from reduced faults and failures (AL), reduced downtime ($Down$), reduced defects (Def), reduced inventory to buffer delays (Inv), and reduced lost sales ($LSales$) multiplied by the percent cost reduction:

$$AM = CR * (AL + Down + Def + Inv) + LSales$$

$$AL = AL_{Ratio} * SHIP_{ASM}$$

$$Down = RM * PercDown * WIP$$

$$Def = PercDef * (MP + PS + PE + PL + Mach + OMT)$$

$$Inv = PercInv * PS$$

$$LSales = \left(\frac{CR * SHIP_{ASM}}{(1 - CR)}\right) * \left(LSales_{Def} + LSales_{Delay}\right)$$

Where

AL_{Ratio} = Ratio of Additional Losses to Shipments from Table 4.3 in Thomas and Weiss (2020). Note that from the table, ID 10 through 13 were utilized, where ID 13 was applied to those NAICS codes not covered by the table.

$SHIP_{ASM}$ = Shipments from ASM data.

RM = Percent of downtime due to reactive maintenance from Table 5.1 in Thomas and Weiss (2020). Note that ID 14 through ID 17 were used from the table, where ID 17 was applied to those NAICS codes not covered by the table.

$PercDown$ = Percent of Planned Production Time that is Downtime from Table 5.1 in Thomas and Weiss (2020). Note that ID 14 through ID 17 were used from the table, where ID 17 was applied to those NAICS codes not covered by the table.

$PercDef$ = Percent of defects due to reactive maintenance Downtime from Table 5.2 in Thomas and Weiss (2020). Note that ID 14 through ID 17 were used from the table, where ID 17 was applied to those NAICS codes not covered by the table.

$PercInv$ = Percent of inventory due to maintenance Downtime from Table 4.4 in Thomas and Weiss (2020). Note that ID 10 through ID 13 were used from the table, where ID 13 was applied to those NAICS codes not covered by the table.

$LSales_{Def}$ = Percent of lost sales attributed to defects resulting from inadequate machinery maintenance from Table 5.3 in Thomas and Weiss (2020). Note that ID 14 through ID 17 were used from the table, where ID 17 was applied to those NAICS codes not covered by the table.

$LSales_{Delay}$ = Percent of lost sales attributed to delays resulting from inadequate machinery maintenance from Table 5.3 in Thomas and Weiss (2020). Note that ID 14 through ID 17 were used from the table, where ID 17 was applied to those NAICS codes not covered by the table.

Table 5.4 provides an estimate of an arbitrary 1 % reduction in losses/costs due to inadequate maintenance. Note that a multiplier is needed to estimate the total reduction in losses/costs. The total estimated 1 % savings is $3.7 billion, which amounts to 0.07 % of shipments, 0.174 % of value added, and 0.353 % of profits. Much of these savings would overlap with those in Section 5.2.1 except for savings due to a decrease in lost sales.

5.2.3. Inventory Management

Determining the level of inventory to maintain involves forecasting or predicting deliveries and sales. Many of the common approaches do not involve complex mathematics but rather might include using moving averages. The methods might be a little more complex by utilizing regression analysis. A more advanced examination might include a digital twin; however, the data that is likely needed for such a model might be difficult to gather for some manufacturers. A large manufacturer that is producing and shipping items from its own facilities to its own facilities or one that can demand information from its suppliers is likely to benefit more from

Table 5.4: Savings from a 1 % Reduction in Losses/Costs Due to Inadequate Maintenance

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from a 1 % Decrease in Losses due to Inadequate maintenance	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	642.2	0.078%	0.219%	0.378%
312	156 041	91 160	70 024	116.3	0.075%	0.128%	0.166%
313	24 531	9 665	4 256	19.9	0.081%	0.206%	0.468%
314	21 286	9 608	4 036	19.3	0.091%	0.201%	0.477%
315	8 428	4 187	1 378	9.3	0.111%	0.223%	0.678%
316	4 009	1 840	505	3.6	0.090%	0.195%	0.712%
321	117 715	49 558	23 225	93.5	0.079%	0.189%	0.403%
322	180 344	68 877	34 436	144.2	0.080%	0.209%	0.419%
323	74 428	38 521	13 181	77.4	0.104%	0.201%	0.587%
324	361 888	50 025	22 848	213.9	0.059%	0.428%	0.936%
325	696 046	352 469	247 307	548.2	0.079%	0.156%	0.222%
326	235 404	103 839	45 516	213.4	0.091%	0.205%	0.469%
327	132 981	66 577	33 871	107.5	0.081%	0.161%	0.317%
331	200 919	63 404	27 489	146.1	0.073%	0.230%	0.532%
332	347 336	169 391	62 450	326.3	0.094%	0.193%	0.523%
333	355 335	156 243	59 554	243.9	0.069%	0.156%	0.409%
334	312 277	154 292	56 323	235.7	0.075%	0.153%	0.418%
335	128 342	58 971	27 424	52.7	0.041%	0.089%	0.192%
336	821 412	250 415	84 331	300.3	0.037%	0.120%	0.356%
337	68 999	33 333	11 994	69.8	0.101%	0.209%	0.582%
339	146 475	81 890	39 683	85.2	0.058%	0.104%	0.215%
High	827 132	352 469	247 307	642.2	0.111%	0.428%	0.936%
Low	4 009	1 840	505	3.6	0.037%	0.089%	0.166%
Median	156 041	66 577	33 871	116.3	0.079%	0.195%	0.419%
Mean	248 635	100 354	49 521	174.7	0.078%	0.189%	0.450%
TOTAL	5 221 325	2 107 441	1 039 932	3 668.5	0.070%*	0.174%*	0.353%*

* Calculated from the total of all manufacturing

this approach than a small manufacturer that would struggle to gather information from their suppliers. The benefits of a digital twin for inventory management include, but are not limited to the following:

- Increase in potential accuracy in predicting material delivery (upstream and/or downstream)
- Reduced inventory needed to buffer delays
- Reduced risk of downtime due to delivery delays
- Shorter delivery times
- Fewer supply chain disruptions

Some insight in inventory management investments might be gained from the Department of Energy (DOE) Industrial Assessment Center (IAC) program. The program has a publicly available database of 148 000 recommendations for 20 000 facilities, as of October 2021. The data is the result of DOE technical assessments of facilities conducted by university engineering students and staff from 26 IACs made up of 31 universities (Industrial Assessment Center 2021; U.S. Department of Energy 2011). Each observation in the IAC database is a recommendation for an investment. It includes an Assessment Recommendation Code (ARC), the cost to implement the recommendation, estimated annual savings, year, whether the recommendation was implemented, and some characteristics of the establishment including sales, various energy expenditures, and number of employees. For the IAC to conduct an assessment, a facility must generally have the following: gross annual sales of $100 million or less, consume energy at a cost greater than $100 000 and less than $2.5 million per year, employ no more than 500 people, and have no technical staff whose primary duty is energy analysis (U.S. Department of Energy 2011). These requirements suggest that the facilities being examined are likely to have a relatively higher level of low-cost, high-return investment possibilities, as these establishments have higher costs (i.e., energy costs) and fewer resources to identify potential investments. The final selection is left up to the individual IACs.

Using the IAC data, the net present value (NPV) and internal rate of return of each ARC recommendation code for inventory controls (ARC 4.32) was calculated for a 10-year study period using data from the IAC, as estimated in Thomas (2022). The results are presented in Table 5.5. Note that some had a negative NPV and/or IRR, where a longer study period would likely result in positive returns. The NPV for these investments ranged between $-32 thousand to $9 million. The NPV equates to between -0.21 % to 19.31 % of the sales of the organizations.

An estimate of a 1 % savings in inventory space can be calculated similar to how production space was estimated:

$$IS = CR * \left(PBM + 0.5 * \left(C_{Bldg} + C_{Bldg\ Rent} + BL + E_{Bldg}\right)\right)$$

Where

IS = Savings from a 1 % reduction in inventory space

In addition to examining the IAC data, one can estimate cost savings that result from a 1 % decrease in inventory. Table 5.6 provides estimates of a 1 % reduction in inventory space by three-digit NAICS codes. For the three-digit NAICS codes, the highest savings from a 1 % reduction is $55 million while the lowest is $0.4 million. The total for manufacturing is $388.0 million, which equates to 0.007 % of shipments, 0.018 % of value added, and 0.037 % of profit. The rule of thumb is that carrying costs are typically 20 % of the value of inventory (Tuovila 2019; Wasp Barcode Technologies 2020). If this rule is accurate, the costs in Table 5.6 are likely an underestimate, as estimating a similar value for manufacturing using the 20 % rule results in an estimate that is about 2.3 times larger than the total for manufacturing in Table 5.6. The source of this difference is likely that the data in the table excludes insurance, depreciation, shrinkage, damage/spoiled inventory, and obsolescence.

Table 5.5: Economic Analysis of Investments in Inventory Controls (ARC 4.32), 2000-2020

Measure	Sales ($million)	Employees	NPV ($1000s)	NPV as a percent of Sales	IRR	Investment ($1000s)	Ten Year Annual Benefit ($1000s)
Average	36.06	152	588.3	2.02%	1241%	28.9	79.9
Median	20.00	122	149.3	0.74%	191%	8.5	22.5
Minimum	1.00	11	-31.8	-0.21%	-87%	303.0	0.0
Maximum	400.00	600	9 019.2	19.31%	22800%	1.0	1 170.0
Total	4 002.71	14 592	65 299.1	1.63%	-	3 212.3	88 660.4

NOTE: This analysis was for investment recommendations in inventory controls where the investment was at least $1000, the firm had at least $1 in sales, and had at least 1 employee. This resulted in 111 recommendations for 106 firms out of 10 356 establishments visited.

5.2.4. Product Design and Development

Digital twins can aid in the design of products. Some products benefit more than others from improved designs, particularly those that involve complex systems. The benefits of improved product design and development can include, but are not limited to the following:

- Shorter design times
    - Reduced engineering costs
- Fewer prototypes and higher first-pass yield
- Decrease in redesigns needed
- Higher quality product
    - Increased customer satisfaction
    - Increased sales

In conversations with R&D leaders, Argolini et al. (2023) reported that some have cut development times by 20 % to 50 %, reducing the costs of design and development. Some also

Table 5.6: Cost Savings from a 1 % Decrease in Building space for Inventory

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Inventory Space	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	55.0	0.007%	0.019%	0.032%
312	156 041	91 160	70 024	10.5	0.007%	0.011%	0.015%
313	24 531	9 665	4 256	1.9	0.008%	0.020%	0.046%
314	21 286	9 608	4 036	2.3	0.011%	0.024%	0.056%
315	8 428	4 187	1 378	1.4	0.016%	0.033%	0.099%
316	4 009	1 840	505	0.4	0.010%	0.021%	0.077%
321	117 715	49 558	23 225	8.6	0.007%	0.017%	0.037%
322	180 344	68 877	34 436	13.7	0.008%	0.020%	0.040%
323	74 428	38 521	13 181	10.1	0.014%	0.026%	0.077%
324	361 888	50 025	22 848	9.0	0.002%	0.018%	0.039%
325	696 046	352 469	247 307	53.8	0.008%	0.015%	0.022%
326	235 404	103 839	45 516	25.0	0.011%	0.024%	0.055%
327	132 981	66 577	33 871	10.6	0.008%	0.016%	0.031%
331	200 919	63 404	27 489	11.5	0.006%	0.018%	0.042%
332	347 336	169 391	62 450	38.3	0.011%	0.023%	0.061%
333	355 335	156 243	59 554	30.1	0.008%	0.019%	0.051%
334	312 277	154 292	56 323	33.1	0.011%	0.021%	0.059%
335	128 342	58 971	27 424	7.7	0.006%	0.013%	0.028%
336	821 412	250 415	84 331	39.3	0.005%	0.016%	0.047%
337	68 999	33 333	11 994	9.1	0.013%	0.027%	0.076%
339	146 475	81 890	39 683	16.6	0.011%	0.020%	0.042%
High	827 132	352 469	247 307	55.0	0.016%	0.033%	0.099%
Low	4 009	1 840	505	0.4	0.002%	0.011%	0.015%
Median	156 041	66 577	33 871	10.6	0.008%	0.020%	0.046%
Mean	248 635	100 354	49 521	18.5	0.009%	0.020%	0.049%
TOTAL	5 221 325	2 107 441	1 039 932	388.0	0.007%*	0.018%*	0.037%*

reported that they needed fewer prototypes and had 25 % fewer quality issues and 3 % to 5 % higher sales. Based on data from Siemens, aerospace companies that employ digital twins have improved first-pass yield to 75 % for designs, reducing physical testing by 25 % (Careless 2021). Altum RF, which produces high-performance radio frequency semiconductor components such as those for 5G networks, reduced its design process by 30 % (Hodge 2023). In this instance, digital twins increased collaboration by creating real-time visibility of progress and changes. It also allowed for first-pass success where, rather than producing prototypes that failed and redesigned, the first prototype was successful.

A recent case study that is relevant to the quality of design data is found in the 787 Dreamliner where Boeing took a new approach for production. While Boeing's previous production methods custom-built each airplane at a single location, Airbus had embraced modular design where subassemblies were manufactured offsite and then shipped to one location for assembly. Boeing had decided to adopt a similar method of production for the 787 Dreamliner where subassemblies would be sourced from other companies. Sections of the plane would be built all over the world with the forward fuselage built in Japan, the wingtips from Korea, the center fuselage from Italy, and other parts from Australia, England, Sweden, and the United States.

This method would require rapid, efficient, and accurate transfer of design data for any changes in design. It was believed that this approach would reduce development costs from $10 billion to $6 billion and reduce development time from 6 to 4 years. Ultimately, the project was billions of dollars over budget and 3 years behind schedule. The first airplane was delivered 40 months behind schedule (McDonald and Kotha 2015).

It has been suggested that the success of modular design relies on the design being set by the Original Equipment Manufacturer (OEM) early on and on subassembly manufacturers having the flexibility to make changes on their own initiative, as long as it does not reduce performance (Sarkar 2017 pg 39-43). Boeing, unexpectedly, had to send hundreds of engineers to its Tier-1, Tier-2, and Tier-3 suppliers to support on-site quality, supplier management, and technical support (Denning 2013). The company had to redesign the entire aircraft sub-assembly process. One of the problems was that some parts did not fit together resulting in extensive rework. Boeing had to purchase some of its suppliers and bring some work back in-house. One of the problems was traced back to the failure to clearly communicate requirements and data to suppliers (Sarkar 2017 pg 42).

Supply-management executive Ben Funston at Boeing said that they, "needed a tool to give us situational awareness into the production system, the ability to have early issue detection and real-time problem resolution" (McDonald and Kotha 2015). This type of solution requires a complete understanding of the production system. Boeing created a Production Integration Center (PIC) to achieve this goal. This center monitored conditions around the world and served as a call center to resolve problems as they arose at supplier locations. Information from Boeing's partners was used to develop routines and graphic-display techniques to monitor manufacturing processes around the globe. Addressing both design and production issues, PIC improved communication and collaboration, making it pivotal in stabilizing Boeing's 787 supply chain.

Another example of design cost savings resulting from modeling might be found in the Integrated Manufacturing Technology Initiative (IMTI), a member-based organization that supports technology advancements in US manufacturing. Discussions within this organization indicated cost reductions from model-based tools have exceeded 50 %. In DoD ground vehicles, for example, production development was reduced from 2 years to 90 or 120 days. In construction equipment, a manufacturer indicated that product development time was reduced from 27 months to 9 months. Boeing reported 91 % time savings and 71 % labor cost savings due to model-based tools. BAE systems reported time savings of seven-fold. Proctor and Gamble documented savings exceeding $1 billion annually with 30 % to 40 % improvement in equipment reliability and 60 % to 70 % faster startup for new equipment and product initiatives (Integrated Manufacturing Technology Initiative, Inc 2009). Major defense contractors from the US MBE team estimated that the implementation of the Model-Based Enterprise would cut costs by 50 % and reduce time to market by 45 %; however, this estimate seems to be a best guess rather than the result of data analysis (IMTI, inc 2009).

An additional benefit of digital twins might be the standardization of data required for adoption. Currently, 3D models are not widely adopted for product designs according to research by Lifecycle Insights. Implementing a digital twin typically requires standardizing data across the system being analyzed. A possible benefit might be the reduction in design communication errors. Thomas (2019) that this type of modeling data can reduce redundant activities that include an estimated $8.40 billion spent on engineers answering questions and creating additional drawing documentation and $3.84 billion for machinists to do the same.

Similar to previous sections, a 1 % reduction in costs is estimated. For research and development costs in manufacturing, this report used input-output data from the Bureau of Economic analysis:

$$RD = CR\frac{RD_{IO\ Use} + RD_{IO\ Make}}{SHIP_{IO}} SHIP_{ASM}$$

where

RD = Research and development costs saved

$RD_{IO\ Use}$ = Sum of research and development from the BEA Use table (U.S. Bureau of Economic Analysis 2024)

$RD_{IO\ Make}$ = Sum of research and development from the BEA Make table (U.S. Bureau of Economic Analysis 2024)

$SHIP_{IO}$ = Sum of shipments from the BEA Use table (U.S. Bureau of Economic Analysis 2024)

Research and development are its own NAICS code (NAICS 541700). Economic data is gathered by establishment, which is a physical location where economic activity occurs, and each establishment is categorized by a NAICS code. The sum of the economic data for all the establishments in a NAICS code makes up the data for that industry. The BEA “Use table” provides estimates from establishments made by NAICS codes separate from manufacturing; however, the BEA “Make Table” provides estimates of activities that would be categorized as NAICS 541700 but occur at establishments with a different NAICS code.

5.2.5. Total Industry Benefits

To estimate the total benefits of data tracking, analysis, modeling, and digital twins, the sum of the benefits shown in Table 5.2, Table 5.4, Table 5.6, and Table 5.7 can be combined. These each show the cost savings for a 1 % decrease in costs. Table 5.8 provides an estimate of the percent reduction in shop floor production costs that result from smart manufacturing developments, calculated from NIST GCR 16-007 (Gallaher et al 2016). These include the following:

- Managing digital data streams through models
- Sensing and monitoring
- Seamless transmission of digital data
- Advanced data and trend analysis
- Communicating information to decision-makers
- Determining required action and implementing action

These items will be referred to as data tracking and analytics. These percent reductions were applied to the categories listed in Table 5.8 to create the savings estimates in Table 5.9. Note that NIST GCR 16-007 estimates that the reductions only apply to approximately 64 % of manufacturing shipments, which is applied to the estimates in Table 5.9 when calculating the total impact. The total estimated savings from data tracking and analytics were estimated to be $88.6 billion, as shown in the table. The table breaks savings into nine categories: onsite material transport, machinery, production labor, energy for production, production space, materials and packaging, maintenance, research and development (R&D) expenditures, and inventory space.

There are two additional categories in the table. Work-in-process flow time, which is not included in the total as it would double-count other categories, and advanced maintenance that is partially excluded from the total for the same reason. The savings amounts to 1.70 % of shipments or revenue and 4.20 % of value added. It would be the equivalent of an 8.52 % increase in net income or profit for all of manufacturing.

It is not clear what proportion of the savings in Table 5.9 is attributable to digital twins, as opposed to data tracking and analytics that have less accuracy, precision, and/or flexibility; however, some insight might be gained from examining high-performing investments. For instance, predictive maintenance is estimated to be 17.3 % of maintenance expenditures (Thomas and Weiss 2020). Another example might be in education, where those with advanced or professional degrees represent 14 % of those aged 25 or older (U.S. Census Bureau 2023). Additionally, the Pareto principle posits that 80 % of a consequence is due to approximately 20 % of the cause (Hopp and Spearman 2008). This is not strictly true, but there is a tendency for this to occur and it has been observed in investment returns (Thomas 2022) and manufacturing costs (Thomas et al. 2017). Moreover, higher-performing categories often represent between 10 % and 20 % of the investments. Thus, it might be reasonable to surmise

Table 5.7: Savings from a 1 % Decrease in R&D Costs

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in R&D Costs	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	28.2	0.003%	0.010%	0.017%
312	156 041	91 160	70 024	5.0	0.003%	0.005%	0.007%
313	24 531	9 665	4 256	1.7	0.007%	0.018%	0.041%
314	21 286	9 608	4 036	1.0	0.005%	0.010%	0.024%
315	8 428	4 187	1 378	1.4	0.017%	0.033%	0.102%
316	4 009	1 840	505	0.5	0.013%	0.029%	0.105%
321	117 715	49 558	23 225	1.3	0.001%	0.003%	0.006%
322	180 344	68 877	34 436	7.6	0.004%	0.011%	0.022%
323	74 428	38 521	13 181	1.3	0.002%	0.003%	0.010%
324	361 888	50 025	22 848	1.4	0.000%	0.003%	0.006%
325	696 046	352 469	247 307	417.1	0.060%	0.118%	0.169%
326	235 404	103 839	45 516	21.5	0.009%	0.021%	0.047%
327	132 981	66 577	33 871	8.1	0.006%	0.012%	0.024%
331	200 919	63 404	27 489	5.1	0.003%	0.008%	0.019%
332	347 336	169 391	62 450	30.2	0.009%	0.018%	0.048%
333	355 335	156 243	59 554	73.9	0.021%	0.047%	0.124%
334	312 277	154 292	56 323	429.7	0.138%	0.278%	0.763%
335	128 342	58 971	27 424	24.7	0.019%	0.042%	0.090%
336	821 412	250 415	84 331	302.0	0.037%	0.121%	0.358%
337	68 999	33 333	11 994	2.6	0.004%	0.008%	0.021%
339	146 475	81 890	39 683	84.5	0.058%	0.103%	0.213%
High	827 132	352 469	247 307	429.7	0.138%	0.278%	0.763%
Low	4 009	1 840	505	0.5	0.000%	0.003%	0.006%
Median	156 041	66 577	33 871	7.6	0.007%	0.018%	0.041%
Mean	248 635	100 354	49 521	69.0	0.020%	0.043%	0.105%
TOTAL	5 221 325	2 107 441	1 039 932	1 448.6	0.028%*	0.069%*	0.139%*

* Calculated from totals and equals the savings as a percent of total shipments, value added, or profit.

Table 5.8: Effective Savings in Shop Floor Production from Smart Manufacturing

	Process Manufacturing (NAICS 311-312, 324-326)	Discrete Manufacturing (NAICS 313-323,327-339)	Categories applied to
Capital	2.15%	11.87%	Machinery, Production Space, Inventory Space
Labor	4.78%	12.32%	Onsite Material Transport, Production Labor, R&D Expenditures, Maintenance
Energy	2.54%	11.17%	Energy for Production
Materials	1.72%	1.98%	Materials and Packaging

NOTE: Calculated by first estimating the expenditures on capital, labor, energy, and materials, which was calculated by taking the "KLEM national factor expenditures" from Table 4-4 in NIST GCR 16-007 and multiplying it by the proportions for capital, labor, energy, and materials found in Figure 4-4 of the same document. The capital, labor, energy, and materials cost impacts were divided by the estimated total expenditures to get the values above. Note that these savings are for "shop floor production."

NOTE: According to Figure 4-4 in NIST GCR 16-007, the impacts are estimated to be applicable to $3 743.9 billion of the estimated $5 846.8 billion in shipments from the 2013 Annual Survey of Manufactures. Thus, after applying the percentages above, the resulting values are multiplied by approximately 0.64 (i.e., the proportion that was estimated to be applicable).

that the top data tracking and analytics investments – those that are or approach being a digital twin that has high levels of accuracy, precision, and flexibility – represent between 10 % and 20 % of the models. Appendix B provides an examination of the return-on-investment trends based on the percentile of the investment costs. An examination of trends in manufacturing investments reveals a strong trend in the proportion of savings, which is shown in Figure B. 1 in Appendix B. Assuming or defining digital twins as the highest cost investments within data tracking and analytics investments can facilitate estimating an expected impact based on the trends in Figure B. 1.

Table 5.10 provides an estimate of the impact or cost/loss savings that might result from the implementation of digital twins in U.S. manufacturing. It assumes that digital twins represent between the top 10 % and 20 % of data tracking and analytics investments by cost. Based on the lower bound 90 % confidence interval from Figure B. 1 for 10 % and the upper bound 90 % confidence interval for 20 %, the range of impact for digital twins is estimated to be between $21.6 billion and $ 53.5 billion with the average value (i.e., 15 %) being $37.9 billion. Figure 5.1 provides the results of relaxing this assumption further to between 1 % and 20 % of data tracking and analytics investment costs. It provides the estimated impact from digital twins based on the average and 90 % confidence intervals estimated from the examination in Appendix B.

To relax other assumptions of this analysis, a Monte Carlo analysis was conducted to consider variations in the inputs for estimating the impact of digital twins. The Monte Carlo analysis varies the rates of capital, labor, energy, and materials reduction due to data tracking and

Table 5.9: Estimated Cost/Loss Savings from Data Analysis, Modeling, and Digital Twins ($millions/year)

		Among Three Digit NAICS				
		High	Low	Median	Mean	TOTAL
Industry Total	*Shipments ($million)*	*529 643*	*2 567*	*99 919*	*159 210*	*3 343 406*
	Value Added ($million)	*225 699*	*1 178*	*42 632*	*64 261*	*1 349 472*
	Profit ($million)	*158 360*	*323*	*21 689*	*31 710*	*665 907*
Savings from Data Analysis, Modeling, and Digital Twins	Onsite Material Transport	244.7	2.8	62.2	79.2	1 664.0
	As a Percent of Shipments	0.13%	0.00%	0.04%	0.05%	0.03%
	As a Percent of Value Added	0.30%	0.01%	0.08%	0.11%	0.08%
	As a Percent of Profit	0.65%	0.02%	0.21%	0.27%	0.16%
	Machinery	1 206.6	3.9	190.9	296.1	6 217.2
	As a Percent of Shipments	0.32%	0.02%	0.15%	0.14%	0.12%
	As a Percent of Value Added	0.84%	0.04%	0.33%	0.34%	0.30%
	As a Percent of Profit	1.85%	0.05%	0.83%	0.82%	0.60%
	Production Labor	4 568.8	44.6	770.7	1 086.3	22 812.6
	As a Percent of Shipments	1.15%	0.05%	0.61%	0.63%	0.44%
	As a Percent of Value Added	2.42%	0.15%	1.49%	1.43%	1.08%
	As a Percent of Profit	8.83%	0.19%	3.17%	3.69%	2.19%
	Energy for Production	402.4	2.1	92.7	120.2	2 524.7
	As a Percent of Shipments	0.24%	0.01%	0.04%	0.07%	0.05%
	As a Percent of Value Added	0.63%	0.01%	0.10%	0.17%	0.12%
	As a Percent of Profit	1.46%	0.02%	0.27%	0.40%	0.24%
	Production Space	310.1	3.2	78.4	100.2	2 103.8
	As a Percent of Shipments	0.13%	0.00%	0.06%	0.06%	0.04%
	As a Percent of Value Added	0.26%	0.02%	0.15%	0.13%	0.10%
	As a Percent of Profit	0.78%	0.02%	0.34%	0.34%	0.20%
	Materials and Packaging	6 623.5	20.1	736.5	1 473.4	30 940.4
	As a Percent of Shipments	0.81%	0.36%	0.53%	0.55%	0.59%
	As a Percent of Value Added	5.89%	0.62%	1.12%	1.49%	1.47%
	As a Percent of Profit	12.90%	0.81%	2.93%	3.51%	2.98%
	Maintenance	1 019.4	4.6	213.3	274.3	5 761.3
	As a Percent of Shipments	0.29%	0.04%	0.12%	0.13%	0.11%
	As a Percent of Value Added	0.79%	0.07%	0.26%	0.33%	0.27%
	As a Percent of Profit	1.83%	0.09%	0.76%	0.77%	0.55%
	R&D Expenditures	3 389.5	4.2	60.0	435.4	9 143.5
	As a Percent of Shipments	1.09%	0.00%	0.05%	0.14%	0.18%
	As a Percent of Value Added	2.20%	0.01%	0.10%	0.30%	0.43%
	As a Percent of Profit	6.02%	0.02%	0.19%	0.78%	0.88%
	Inventory Space	310.1	3.2	78.4	100.2	2 103.8
	As a Percent of Shipments	0.13%	0.00%	0.06%	0.06%	0.04%
	As a Percent of Value Added	0.26%	0.02%	0.15%	0.13%	0.10%
	As a Percent of Profit	0.78%	0.02%	0.34%	0.34%	0.20%
	WIP Flow Time	*6 081.3*	*51.7*	*1 002.1*	*1 482.6*	*31 133.6*
	As a Percent of Shipments	*1.42%*	*0.09%*	*0.85%*	*0.84%*	*0.60%*
	As a Percent of Value Added	*2.94%*	*0.21%*	*2.25%*	*1.90%*	*1.48%*
	As a Percent of Profit	*10.24%*	*0.27%*	*4.91%*	*4.85%*	*2.99%*
	Advanced Maintenance	*850.2*	*9.5*	*236.4*	*308.1*	*6 469.7*
	As a Percent of Shipments	*0.25%*	*0.07%*	*0.20%*	*0.17%*	*0.12%*
	As a Percent of Value Added	*0.62%*	*0.13%*	*0.47%*	*0.39%*	*0.31%*
	As a Percent of Profit	*1.88%*	*0.16%*	*1.03%*	*0.96%*	*0.62%*
	Total*	18 075	89	2 283	3 965	88 610
	As a Percent of Shipments	0.35%	0.00%	0.04%	0.08%	1.70%
	As a Percent of Value Added	0.86%	0.00%	0.11%	0.19%	4.20%
	As a Percent of Profit	1.74%	0.01%	0.22%	0.38%	8.52%

* Excludes WIP Flow Time, as it would double count items from other categories

Table 5.10: Estimated Cost/Loss Savings from Digital Twins ($millions/year)

	Pareto Principal Range	90 % Confidence Interval (Lower Bound)	Average	90 % Confidence Interval (Upper Bound)
Impact from Digital Twins	Onsite Material Transport	405.0	711.7	1 004.5
	As a Percent of Shipments	0.01%	0.01%	0.02%
	As a Percent of Value Added	0.02%	0.03%	0.05%
	As a Percent of Profit	0.04%	0.07%	0.10%
	Machinery	1 513.4	2 659.3	3 753.0
	As a Percent of Shipments	0.03%	0.05%	0.07%
	As a Percent of Value Added	0.07%	0.13%	0.18%
	As a Percent of Profit	0.15%	0.26%	0.36%
	Production Labor	5 553.1	9 757.7	13 770.9
	As a Percent of Shipments	0.11%	0.19%	0.26%
	As a Percent of Value Added	0.26%	0.46%	0.65%
	As a Percent of Profit	0.53%	0.94%	1.32%
	Energy for Production	614.6	1 079.9	1 524.0
	As a Percent of Shipments	0.01%	0.02%	0.03%
	As a Percent of Value Added	0.03%	0.05%	0.07%
	As a Percent of Profit	0.06%	0.10%	0.15%
	Production Space	512.1	899.9	1 269.9
	As a Percent of Shipments	0.01%	0.02%	0.02%
	As a Percent of Value Added	0.02%	0.04%	0.06%
	As a Percent of Profit	0.05%	0.09%	0.12%
	Materials and Packaging	7 531.6	13 234.3	18 677.2
	As a Percent of Shipments	0.14%	0.25%	0.36%
	As a Percent of Value Added	0.36%	0.63%	0.89%
	As a Percent of Profit	0.72%	1.27%	1.80%
	Maintenance	1 402.4	2 464.3	3 477.8
	As a Percent of Shipments	0.03%	0.05%	0.07%
	As a Percent of Value Added	0.07%	0.12%	0.17%
	As a Percent of Profit	0.13%	0.24%	0.33%
	R&D Expenditures	2 225.7	3 911.0	5 519.5
	As a Percent of Shipments	0.04%	0.07%	0.11%
	As a Percent of Value Added	0.11%	0.19%	0.26%
	As a Percent of Profit	0.21%	0.38%	0.53%
	Inventory Space	512.1	899.9	1 269.9
	As a Percent of Shipments	0.01%	0.02%	0.02%
	As a Percent of Value Added	0.02%	0.04%	0.06%
	As a Percent of Profit	0.05%	0.09%	0.12%
	WIP Flow Time	*7 578.6*	*13 316.9*	*18 793.8*
	As a Percent of Shipments	*0.15%*	*0.26%*	*0.36%*
	As a Percent of Value Added	*0.36%*	*0.63%*	*0.89%*
	As a Percent of Profit	*0.73%*	*1.28%*	*1.81%*
	Advanced Maintenance	*1 574.9*	*2 767.3*	*3 905.4*
	As a Percent of Shipments	*0.03%*	*0.05%*	*0.07%*
	As a Percent of Value Added	*0.07%*	*0.13%*	*0.19%*
	As a Percent of Profit	*0.15%*	*0.27%*	*0.38%*
	Total*	21 570	37 902	53 490
	As a Percent of Shipments	0.41%	0.73%	1.02%
	As a Percent of Value Added	1.02%	1.80%	2.54%
	As a Percent of Profit	2.07%	3.64%	5.14%

NOTE: Lower bound estimate is for 10 %, average is at 15 %, and upper bound is for 20 % of the data tracking and analytics investments.

analytics from NIST GCR 16-007 found in Table 5.8 with a lower bound of 50 % of the original value and an upper bound being 20 % higher. The simulation used a triangular distribution. The applicable proportion of manufacturing that is affected by advancements in data tracking and analytics (i.e., 64 %) was varied by -50 % and +20 % also using a triangular distribution. The assumption that digital twins represent between the top 10 % and 20 % of data tracking and analytics investments is varied from 5 % and 20 % using a triangular distribution with 15 % being the most likely value. The calculated labor estimates ($Lab_{Onsite\ Trans}$, Lab_{Prod}, Lab_{Bldg}, $Lab_{Mach\ Maint}$) are varied -50 % and +20 % using a triangular distribution. Figure 5.2 and Figure 5.3 presents the results of one thousand iterations of the Monte Carlo simulation with the former presenting the dollar impacts for both data tracking/analysis and digital twins. The latter presents the percent of shipments, value added, and profit that the digital twins impact represents. The 90 percent confidence interval for the impact of digital twins was between \$16.1 billion and \$38.6 billion with the median being \$27.2 billion. The average (not shown) was also \$27.2 billion. As a percent of manufacturing industry shipments, the 90 percent confidence interval for the impact of digital twins was between 0.33 % and 0.75 % while for value added it is 0.81 % and 1.86 %. As a percentage of profit, it was between 1.63 % and 3.70 %. A reasonable conjecture from the results is that the potential impact of digital twins in the U.S. is in the low tens of billions of dollars. A more precise estimate with higher confidence would likely require data collection from manufacturers.

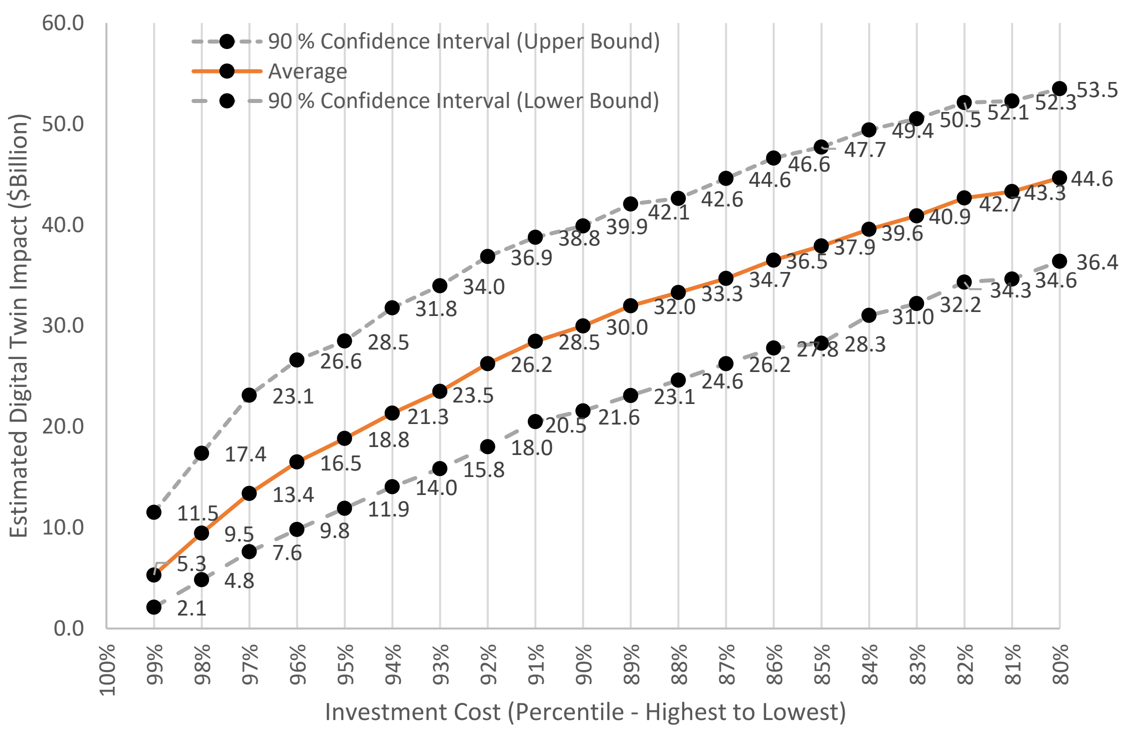


Figure 5.1: Estimated Annual Digital Twin Impact by Varying Levels of Investment Cost (percentile)

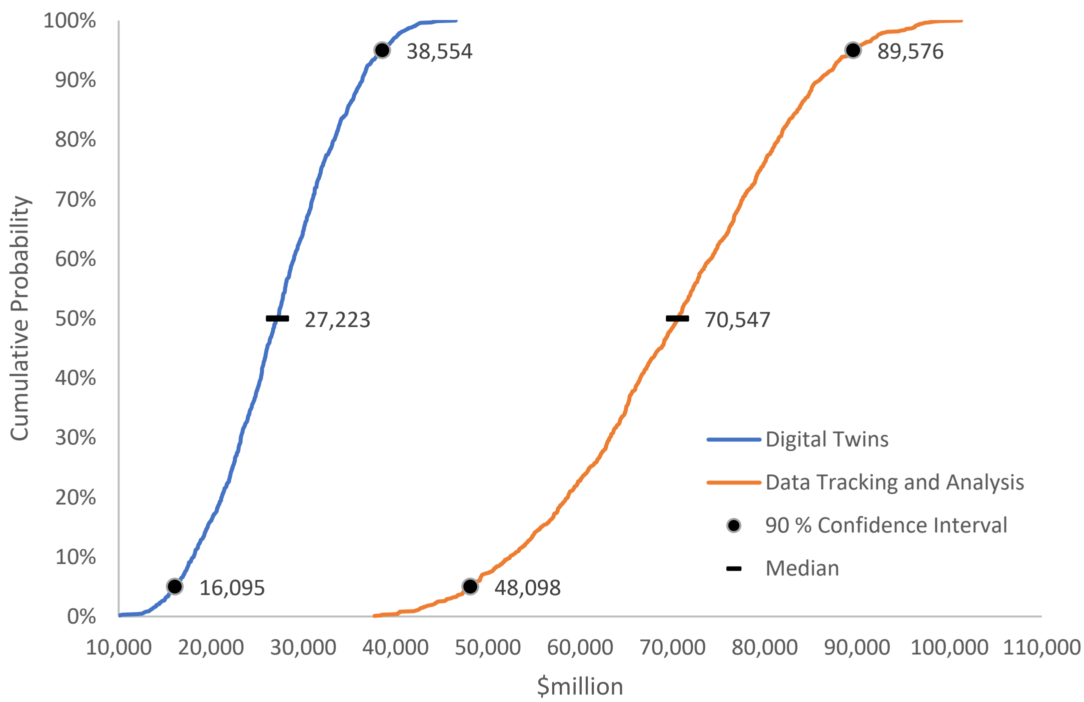


Figure 5.2: Monte Carlo results on the Impact of Digital Twins along with Data Tracking/Analysis

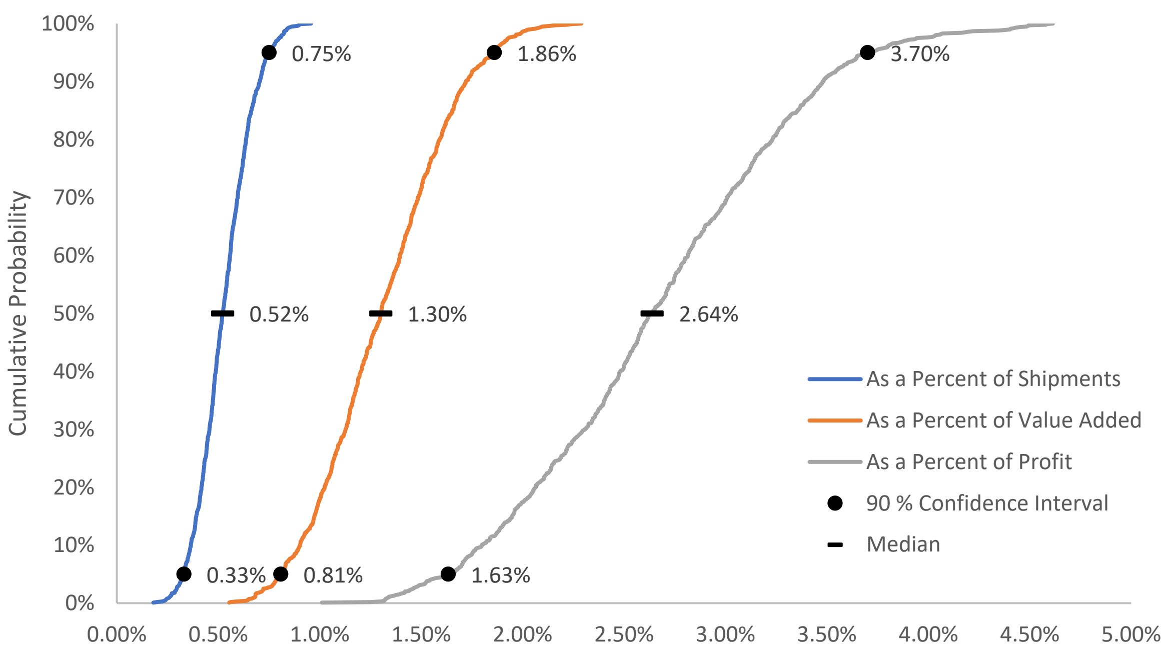


Figure 5.3: Monte Carlo Results on the Impact of Digital Twins as a Percent of Shipments, Value Added, and Profit

6. Summary

This report examined the economics of digital twins in the manufacturing industry, including the costs, benefits, and economic decisions to invest in the adoption of a digital twin. As discussed in Chapter 2, digital twins are used in five primary areas based on the sales of software for implementation (Markets and Markets 2022): predictive maintenance (39.9 %), business optimization (25.3 %), performance monitoring (17.8 %), inventory management (11.9 %), and product design and development (3.4 %). The remaining applications represent 1.6 % of the sales. Three primary factors inhibit their growth: cyber threats, cost, and the required human capital.

As discussed in Chapter 3, digital twins primarily function to make predictions or as an indicator for the system being modeled. The benefit of a digital twin over other models is essentially the increase in accuracy, precision, and flexibility of the model and its predictions. Note that flexibility is the model's ability to consider different types and levels of input factors along with different types and levels of outcomes. The cost-effectiveness of investing in a digital twin is likely affected by the complexity and sensitivity of the real-world system being modeled, along with the cost consequence of having the non-optimal level of settings or design for the system. A digital twin is more likely to be cost effective for a complex system that has a high-cost consequence for having non-optimal settings/designs. As either of these factors (system complexity or the cost consequence of non-optimal settings/designs) decrease, digital twins are likely to become less cost-effective and models or data tracking with less accuracy, precision, and/or flexibility become more cost-effective. Chapter 4 discusses net present value and internal rate of return as methods for investment analysis in digital twins.

As discussed in Chapter 5, data on the costs of digital twins is more concentrated at the individual firm or establishment level while data on the benefits tends to be better at the industry level. The average selling price of a digital twin product or solution for one seat is estimated to be between \$600 to \$800 (Markets and Markets 2022); however, this is just for the software. In a survey of executives from aerospace, defense, automotive, medical device, oil/gas, and consumer electronics, an estimated 86 % spent \$1 million or more annually on digital twins (Dertien and McMahon 2022). If digital twins account for the top 15 % of future data tracking and analytics investments (i.e., those with costs above the 85th percentile), the total potential impact of the adoption of digital twins in the manufacturing industry is estimated to be \$37.9 billion. A Monte Carlo simulation varying key factors of this estimate by -50 % and +20 % (i.e., biasing it downwards) and assuming that digital twins account for between the top 5 % and 20 % of data tracking and analytics investments (i.e., those investments with costs between the 80th and 95th percentile) puts the 90 % confidence interval between \$16.1 billion and \$38.6 billion with a median of \$27.2 billion. The total benefits of all data tracking and analytics investments, including digital twins and those with less precision, accuracy, and flexibility, is estimated to be \$88.6 billion. These industry-level estimates are based on a number of datasets and calculations, including tendencies or patterns in the relationship between the costs and returns on investments DOE Industrial Assessment Center data. From the industry estimates in this report, one could reasonably conclude that the impact is likely in the low tens of billions of dollars. Future research could increase the accuracy and precision of these estimates by collecting additional data from manufacturers.

In order for the benefits of data tracking and analytics investments to be maximized, including those from digital twins, the appropriate level of modeling needs to be selected based on the system complexity and cost consequences of having non-optimal system design/settings. If systems are matched with the inefficient solutions, the total industry impact will be reduced. Moreover, the best practice for data tracking and analytics is not to simply adopt the most advanced methods of modeling, but to match the right model or data solution to each system. This matching requires a method for selecting the right model. This report discusses such a method; however, it is a proposed method that still requires some refinement and vetting. Thus, more research and development is needed.

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Appendix A. Cost Savings Items for Business Optimization

Table A. 1: Annual Savings from a 1 % Decrease in Onsite Material Transportation Cost

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Onsite Transport Costs	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	79.9	0.010%	0.027%	0.047%
312	156 041	91 160	70 024	5.5	0.004%	0.006%	0.008%
313	24 531	9 665	4 256	1.5	0.006%	0.016%	0.036%
314	21 286	9 608	4 036	0.7	0.003%	0.007%	0.017%
315	8 428	4 187	1 378	0.7	0.008%	0.016%	0.049%
316	4 009	1 840	505	0.4	0.009%	0.020%	0.071%
321	117 715	49 558	23 225	19.0	0.016%	0.038%	0.082%
322	180 344	68 877	34 436	17.6	0.010%	0.025%	0.051%
323	74 428	38 521	13 181	8.6	0.012%	0.022%	0.065%
324	361 888	50 025	22 848	2.1	0.001%	0.004%	0.009%
325	696 046	352 469	247 307	15.6	0.002%	0.004%	0.006%
326	235 404	103 839	45 516	25.1	0.011%	0.024%	0.055%
327	132 981	66 577	33 871	14.1	0.011%	0.021%	0.042%
331	200 919	63 404	27 489	13.8	0.007%	0.022%	0.050%
332	347 336	169 391	62 450	24.1	0.007%	0.014%	0.039%
333	355 335	156 243	59 554	12.7	0.004%	0.008%	0.021%
334	312 277	154 292	56 323	4.8	0.002%	0.003%	0.008%
335	128 342	58 971	27 424	6.0	0.005%	0.010%	0.022%
336	821 412	250 415	84 331	22.3	0.003%	0.009%	0.026%
337	68 999	33 333	11 994	7.2	0.010%	0.022%	0.060%
339	146 475	81 890	39 683	7.9	0.005%	0.010%	0.020%
High	827 132	352 469	247 307	79.9	0.016%	0.038%	0.082%
Low	4 009	1 840	505	0.4	0.001%	0.003%	0.006%
Median	156 041	66 577	33 871	8.6	0.007%	0.016%	0.039%
Mean	248 635	100 354	49 521	13.8	0.007%	0.016%	0.037%
TOTAL	5 221 325	2 107 441	1 039 932	289.4	0.006%*	0.014%*	0.028%*

* Calculated from the total of all manufacturing

Table A. 2: Annual Cost Savings from a 1 % Decrease in Production Machinery

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Machinery for Production	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	138.9	0.017%	0.047%	0.082%
312	156 041	91 160	70 024	26.8	0.017%	0.029%	0.038%
313	24 531	9 665	4 256	6.5	0.026%	0.067%	0.152%
314	21 286	9 608	4 036	3.1	0.015%	0.032%	0.077%
315	8 428	4 187	1 378	0.9	0.011%	0.022%	0.066%
316	4 009	1 840	505	0.5	0.013%	0.028%	0.101%
321	117 715	49 558	23 225	25.4	0.022%	0.051%	0.109%
322	180 344	68 877	34 436	75.7	0.042%	0.110%	0.220%
323	74 428	38 521	13 181	18.0	0.024%	0.047%	0.137%
324	361 888	50 025	22 848	86.0	0.024%	0.172%	0.377%
325	696 046	352 469	247 307	215.8	0.031%	0.061%	0.087%
326	235 404	103 839	45 516	77.6	0.033%	0.075%	0.170%
327	132 981	66 577	33 871	41.7	0.031%	0.063%	0.123%
331	200 919	63 404	27 489	67.0	0.033%	0.106%	0.244%
332	347 336	169 391	62 450	87.7	0.025%	0.052%	0.140%
333	355 335	156 243	59 554	74.5	0.021%	0.048%	0.125%
334	312 277	154 292	56 323	98.4	0.032%	0.064%	0.175%
335	128 342	58 971	27 424	18.4	0.014%	0.031%	0.067%
336	821 412	250 415	84 331	158.7	0.019%	0.063%	0.188%
337	68 999	33 333	11 994	14.6	0.021%	0.044%	0.122%
339	146 475	81 890	39 683	28.2	0.019%	0.034%	0.071%
High	827 132	352 469	247 307	215.8	0.042%	0.172%	0.377%
Low	4 009	1 840	505	0.5	0.011%	0.022%	0.038%
Median	156 041	66 577	33 871	41.7	0.022%	0.051%	0.123%
Mean	248 635	100 354	49 521	60.2	0.023%	0.059%	0.137%
TOTAL	5 221 325	2 107 441	1 039 932	1 264.5	0.024%*	0.06%*	0.122%*

* Calculated from the total of all manufacturing

Table A. 3: Annual Cost Savings from a 1 % Decrease in Production Labor

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Labor for Production	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	392.5	0.047%	0.134%	0.231%
312	156 041	91 160	70 024	44.4	0.028%	0.049%	0.063%
313	24 531	9 665	4 256	24.4	0.099%	0.252%	0.573%
314	21 286	9 608	4 036	25.6	0.120%	0.266%	0.634%
315	8 428	4 187	1 378	12.3	0.146%	0.295%	0.895%
316	4 009	1 840	505	5.7	0.141%	0.307%	1.119%
321	117 715	49 558	23 225	93.4	0.079%	0.188%	0.402%
322	180 344	68 877	34 436	127.1	0.070%	0.185%	0.369%
323	74 428	38 521	13 181	97.6	0.131%	0.253%	0.740%
324	361 888	50 025	22 848	59.3	0.016%	0.119%	0.260%
325	696 046	352 469	247 307	251.7	0.036%	0.071%	0.102%
326	235 404	103 839	45 516	243.9	0.104%	0.235%	0.536%
327	132 981	66 577	33 871	90.5	0.068%	0.136%	0.267%
331	200 919	63 404	27 489	140.2	0.070%	0.221%	0.510%
332	347 336	169 391	62 450	495.9	0.143%	0.293%	0.794%
333	355 335	156 243	59 554	343.1	0.097%	0.220%	0.576%
334	312 277	154 292	56 323	131.0	0.042%	0.085%	0.233%
335	128 342	58 971	27 424	99.1	0.077%	0.168%	0.361%
336	821 412	250 415	84 331	579.2	0.071%	0.231%	0.687%
337	68 999	33 333	11 994	100.8	0.146%	0.302%	0.840%
339	146 475	81 890	39 683	141.1	0.096%	0.172%	0.356%
High	827 132	352 469	247 307	579.2	0.146%	0.307%	1.119%
Low	4 009	1 840	505	5.7	0.016%	0.049%	0.063%
Median	156 041	66 577	33 871	100.8	0.079%	0.220%	0.510%
Mean	248 635	100 354	49 521	166.6	0.087%	0.199%	0.502%
TOTAL	5 221 325	2 107 441	1 039 932	3 498.7	0.067%*	0.166%*	0.336%*

* Calculated from the total of all manufacturing

Table A. 4: Annual Cost Savings from a 1 % Reduction in Production Energy

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Energy for Production	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	71.7	0.009%	0.024%	0.042%
312	156 041	91 160	70 024	7.6	0.005%	0.008%	0.011%
313	24 531	9 665	4 256	5.4	0.022%	0.056%	0.126%
314	21 286	9 608	4 036	1.5	0.007%	0.016%	0.038%
315	8 428	4 187	1 378	0.6	0.007%	0.014%	0.041%
316	4 009	1 840	505	0.3	0.007%	0.016%	0.057%
321	117 715	49 558	23 225	17.4	0.015%	0.035%	0.075%
322	180 344	68 877	34 436	50.4	0.028%	0.073%	0.146%
323	74 428	38 521	13 181	6.4	0.009%	0.017%	0.049%
324	361 888	50 025	22 848	61.9	0.017%	0.124%	0.271%
325	696 046	352 469	247 307	138.2	0.020%	0.039%	0.056%
326	235 404	103 839	45 516	31.3	0.013%	0.030%	0.069%
327	132 981	66 577	33 871	45.1	0.034%	0.068%	0.133%
331	200 919	63 404	27 489	56.2	0.028%	0.089%	0.205%
332	347 336	169 391	62 450	30.2	0.009%	0.018%	0.048%
333	355 335	156 243	59 554	13.0	0.004%	0.008%	0.022%
334	312 277	154 292	56 323	18.8	0.006%	0.012%	0.033%
335	128 342	58 971	27 424	6.4	0.005%	0.011%	0.023%
336	821 412	250 415	84 331	23.4	0.003%	0.009%	0.028%
337	68 999	33 333	11 994	2.9	0.004%	0.009%	0.024%
339	146 475	81 890	39 683	4.4	0.003%	0.005%	0.011%
High	827 132	352 469	247 307	138.2	0.034%	0.124%	0.271%
Low	4 009	1 840	505	0.3	0.003%	0.005%	0.011%
Median	156 041	66 577	33 871	17.4	0.009%	0.017%	0.048%
Mean	248 635	100 354	49 521	28.2	0.012%	0.032%	0.072%
TOTAL	5 221 325	2 107 441	1 039 932	593.0	0.011%*	0.028%*	0.057%*

* Calculated from the total of all manufacturing

Table A. 5: Annual Cost Savings from a 1 % Reduction in Production Space

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in Production Space	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	65.2	0.008%	0.022%	0.038%
312	156 041	91 160	70 024	11.1	0.007%	0.012%	0.016%
313	24 531	9 665	4 256	2.0	0.008%	0.021%	0.048%
314	21 286	9 608	4 036	2.3	0.011%	0.024%	0.058%
315	8 428	4 187	1 378	1.4	0.017%	0.034%	0.103%
316	4 009	1 840	505	0.4	0.011%	0.023%	0.084%
321	117 715	49 558	23 225	9.5	0.008%	0.019%	0.041%
322	180 344	68 877	34 436	14.6	0.008%	0.021%	0.042%
323	74 428	38 521	13 181	11.0	0.015%	0.029%	0.084%
324	361 888	50 025	22 848	9.4	0.003%	0.019%	0.041%
325	696 046	352 469	247 307	57.1	0.008%	0.016%	0.023%
326	235 404	103 839	45 516	26.0	0.011%	0.025%	0.057%
327	132 981	66 577	33 871	11.3	0.008%	0.017%	0.033%
331	200 919	63 404	27 489	12.1	0.006%	0.019%	0.044%
332	347 336	169 391	62 450	40.8	0.012%	0.024%	0.065%
333	355 335	156 243	59 554	31.2	0.009%	0.020%	0.052%
334	312 277	154 292	56 323	34.2	0.011%	0.022%	0.061%
335	128 342	58 971	27 424	8.1	0.006%	0.014%	0.030%
336	821 412	250 415	84 331	40.2	0.005%	0.016%	0.048%
337	68 999	33 333	11 994	9.6	0.014%	0.029%	0.080%
339	146 475	81 890	39 683	17.2	0.012%	0.021%	0.043%
High	827 132	352 469	247 307	65.2	0.017%	0.034%	0.103%
Low	4 009	1 840	505	0.4	0.003%	0.012%	0.016%
Median	156 041	66 577	33 871	11.3	0.008%	0.021%	0.048%
Mean	248 635	100 354	49 521	19.8	0.009%	0.021%	0.052%
TOTAL	5 221 325	2 107 441	1 039 932	415.0	0.008%*	0.02%*	0.04%*

* Calculated from the total of all manufacturing

Table A. 6: Annual Cost Savings from a 1 % Reduction in Materials and Packaging

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in R&D Costs	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	4 786.0	0.579%	1.632%	2.814%
312	156 041	91 160	70 024	517.5	0.332%	0.568%	0.739%
313	24 531	9 665	4 256	124.8	0.509%	1.291%	2.933%
314	21 286	9 608	4 036	93.4	0.439%	0.972%	2.314%
315	8 428	4 187	1 378	28.2	0.335%	0.674%	2.047%
316	4 009	1 840	505	15.8	0.395%	0.860%	3.131%
321	117 715	49 558	23 225	571.5	0.485%	1.153%	2.461%
322	180 344	68 877	34 436	877.9	0.487%	1.275%	2.549%
323	74 428	38 521	13 181	262.1	0.352%	0.680%	1.989%
324	361 888	50 025	22 848	2 683.7	0.742%	5.365%	11.746%
325	696 046	352 469	247 307	2 604.3	0.374%	0.739%	1.053%
326	235 404	103 839	45 516	1 059.6	0.450%	1.020%	2.328%
327	132 981	66 577	33 871	486.3	0.366%	0.730%	1.436%
331	200 919	63 404	27 489	1 142.0	0.568%	1.801%	4.154%
332	347 336	169 391	62 450	1 335.0	0.384%	0.788%	2.138%
333	355 335	156 243	59 554	1 580.4	0.445%	1.011%	2.654%
334	312 277	154 292	56 323	1 237.6	0.396%	0.802%	2.197%
335	128 342	58 971	27 424	580.7	0.453%	0.985%	2.118%
336	821 412	250 415	84 331	5 223.0	0.636%	2.086%	6.193%
337	68 999	33 333	11 994	288.1	0.418%	0.864%	2.402%
339	146 475	81 890	39 683	459.7	0.314%	0.561%	1.158%
High	827 132	352 469	247 307	5 223.0	0.742%	5.365%	11.746%
Low	4 009	1 840	505	15.8	0.314%	0.561%	0.739%
Median	156 041	66 577	33 871	580.7	0.439%	0.972%	2.328%
Mean	248 635	100 354	49 521	1 236.1	0.450%	1.231%	2.884%
TOTAL	5 221 325	2 107 441	1 039 932	25 957.7	0.497%*	1.232%*	2.496%*

* Calculated from the total of all manufacturing

Table A. 7: Annual Cost Savings from a 1 % Reduction in Work-in-Process (WIP) Flow Time

NAICS	Shipments ($million)	Value Added ($million)	Profit ($million)	Savings ($million) from 1 % Decrease in WIP Flow Time	Savings as a percent of Shipments	Savings as a percent of Value Added	Savings as a Percent of Profit
311	827 132	293 175	170 102	586.3	0.071%	0.200%	0.345%
312	156 041	91 160	70 024	81.7	0.052%	0.090%	0.117%
313	24 531	9 665	4 256	32.8	0.134%	0.340%	0.771%
314	21 286	9 608	4 036	30.9	0.145%	0.322%	0.767%
315	8 428	4 187	1 378	14.6	0.173%	0.349%	1.060%
316	4 009	1 840	505	6.6	0.163%	0.356%	1.297%
321	117 715	49 558	23 225	127.4	0.108%	0.257%	0.549%
322	180 344	68 877	34 436	216.6	0.120%	0.314%	0.629%
323	74 428	38 521	13 181	125.7	0.169%	0.326%	0.954%
324	361 888	50 025	22 848	154.4	0.043%	0.309%	0.676%
325	696 046	352 469	247 307	521.4	0.075%	0.148%	0.211%
326	235 404	103 839	45 516	346.5	0.147%	0.334%	0.761%
327	132 981	66 577	33 871	142.7	0.107%	0.214%	0.421%
331	200 919	63 404	27 489	218.7	0.109%	0.345%	0.795%
332	347 336	169 391	62 450	621.8	0.179%	0.367%	0.996%
333	355 335	156 243	59 554	447.7	0.126%	0.287%	0.752%
334	312 277	154 292	56 323	262.6	0.084%	0.170%	0.466%
335	128 342	58 971	27 424	125.2	0.098%	0.212%	0.457%
336	821 412	250 415	84 331	777.2	0.095%	0.310%	0.922%
337	68 999	33 333	11 994	124.5	0.180%	0.373%	1.038%
339	146 475	81 890	39 683	185.9	0.127%	0.227%	0.468%
High	827 132	352 469	247 307	777.2	0.180%	0.373%	1.297%
Low	4 009	1 840	505	6.6	0.043%	0.090%	0.117%
Median	156 041	66 577	33 871	154.4	0.120%	0.310%	0.752%
Mean	248 635	100 354	49 521	245.3	0.119%	0.279%	0.688%
TOTAL	5 221 325	2 107 441	1 039 932	5 151.2	0.099%*	0.244%*	0.495%*

* Calculated from the total of all manufacturing

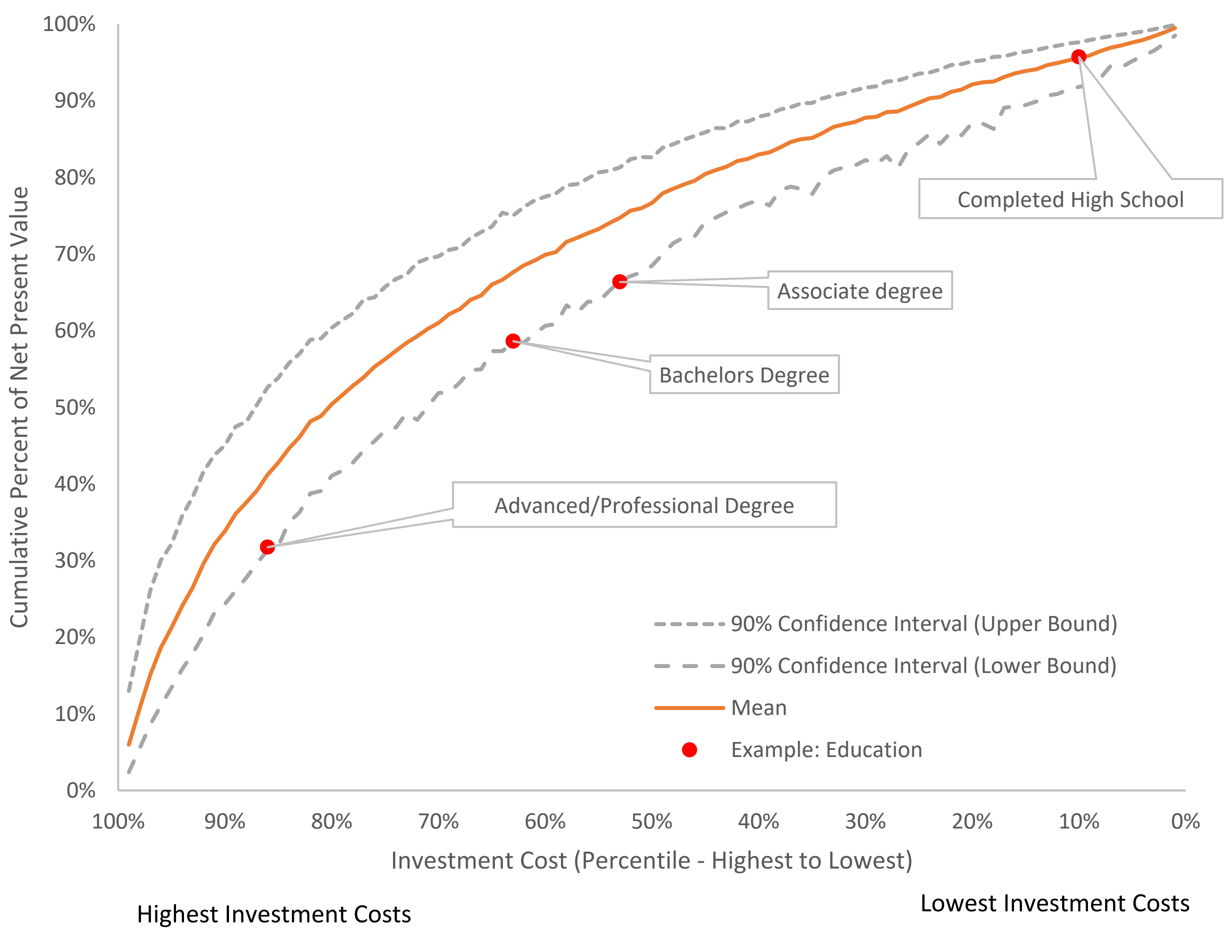
Appendix B. Digital Twins Proportion

The proportion of the impact from Table 5.9 attributed to only digital twins is unknown; however, investment returns tend to follow some trends that can be used to provide an approximation. These trends can be estimated using data from the Industrial Assessment Center (IAC) database, a publicly available database of 148K recommendations for 20K facilities, as of October 2021. The data is the result of DOE technical assessments of facilities conducted by university engineering students and staff from 26 IAC centers made up of 31 universities (Industrial Assessment Center 2021; U.S. Department of Energy 2011). Each observation in the IAC database is a recommendation for an investment. It includes an Assessment Recommendation Code (discussed below), the cost to implement the recommendation, the estimated annual savings, the year, whether the recommendation was implemented, and some characteristics of the establishment including sales, various energy expenditures, and the number of employees. For the IAC to conduct an assessment, a facility must generally have the following: gross annual sales of $100 million or less, consume energy at a cost greater than $100,000 and less than $2.5 million per year, and employ no more than 500 people (U.S. Department of Energy 2011).

The net present value of each recommendation was calculated for a 10-year study period using data from the IAC, as estimated in Thomas (2022). This equates to 81 443 investment analyses from recommendations made by the IAC program. Investment returns tend to follow patterns. For instance, results from Thomas (2022) demonstrate that investment returns follow the Pareto principle, where 20 % of potential investments represent 80 % of the cumulative net present value. This report analyzed patterns between the investment cost and the cumulative net present value. That is, it asks whether higher cost investments (e.g., digital twins) account for a predictable proportion of the benefits for all investments. The motivation for examining this issue is that the data available allows for estimating the impact of all data tracking and analytics investments, but not that for digital twins. However, earlier it was concluded that digital twins represent the highest levels of potential accuracy, precision, and flexibility, making them the highest cost data tracking and analytics investments. If there is a predictable relationship between the cost of an investment and the proportion of impact that it represents, we can use that information to approximate an impact for digital twins.

To test the hypothesis of whether higher cost investments (e.g., digital twins) account for a predictable proportion of the benefits for all investments, one thousand random samples of the IAC data were taken, each with one thousand observations. For each sample, the proportion of benefits that each percentile of investment cost was examined. That is, the relationship between the relative level of investment cost and relative proportion of potential benefits was examined. The results shown in Figure B. 1 suggest that there is a pattern between the investment level and the proportion of the potential benefits. For instance, those investments that are at the 80th percentile in cost on the x-axis (i.e., the top 20 % in investment cost), represent 50.4 % of the potential benefits of all the investments with a 90 % confidence interval between 41.1 % and 60.4 %.

To examine whether this trend applied to investments outside of the IAC data, an anecdotal examination of education was made. Although it is an imperfect test, there are limited examples with available data. For those aged 25 or older, approximately 14 % have an advanced/professional degree, which amounts to the highest 14 % investment in education. Although there are non-monetary returns involved in education (e.g., job security and those who go to seminary), based on Figure B. 1 one might expect the highest 14 % (i.e., 86th percentile) to account for between 31.4 % and 52.6 % of the net benefits for all levels of education for those aged 25 and older. The aggregated annual income for all individuals aged 25 and older was estimated for 30 years discounted at a 5 % rate. The cost of education was estimated and subtracted as an initial investment. Those with an advanced/professional degree account for 32.7 % of the total income, putting it just inside the 90 % confidence interval in Figure B. 1. Similar calculations were made for bachelor's degrees, associates, and high school. The associate degree was the only one that fell outside the confidence interval, but it was only by 0.089 percentage points. Again, this could be due to some benefits being non-financial.



NOTE: Investments that cost $1000 or more with NAICS classification were used.

Data Sources: Census Bureau 2023; Statista 2023

Figure B. 1: IAC Cumulative Net Present Value by Investment Cost (Percentile)

The higher performing categories often represent between 10 % and 20 % of the investments. For instance, predictive maintenance is estimated to be 17.3 % of maintenance expenditures. In education, those with an advanced or professional degrees represent 14 % of those aged 25 or older. Additionally, the pareto principle states that 20 % of the cause represents 80 % of the outcome, again focusing on the top 20 %. Thus, the top performing categories are often between 10 % and 20 % of the total. As discussed in Chapter 3, digital twins approach the highest level of potential accuracy, precision, and flexibility and the highest level of costs for modeling and data analysis. If one assumes that digital twins represent between 10 % and 20 % of the potential investments in data analysis and modeling, then the average percent of the net present value can be estimated from Figure B. 1 and is between 33.8 % and 50.4 %. If one assumes that digital twins represent 15 % of the investments, then the average expected proportion of impact or net present value attributable to digital twins would be 42.8 %, on average.