

Article

Impact of Digitalization on Process Optimization and Decision-Making towards Sustainability: The Moderating Role of Environmental Regulation

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Abstract: Digitalization has brought a significant improvement in process optimization and decision-making processes, in particular in pursuing the goal of sustainability. This study examines how digitalization has affected process optimization and decision-making towards sustainability, focusing on Pakistan's manufacturing sector. This study also examines the moderating role of environmental regulations between digitalization and sustainable practices. This study is based on quantitative methodology. Purposive sampling was used to gather primary data from 554 managers and engineers working in manufacturing industries in Pakistan through a closed-ended questionnaire. Smart PLS was used for data analysis. The findings show digitalization's positive and significant influence on process optimization and decision-making. The results also show that environmental regulations have a significant moderating effect on the digitalization of processes and decision-making towards sustainability practices. The findings provide a guideline for industries, decision-makers, and researchers for developing strategies that effectively use digitalization for sustainability and assist in achieving the Sustainable Development Goals (SGD-9, SGD-11, SGD-12, and SGD-13).

Keywords: digital transformation; environmental regulation; process optimization and decision making; sustainability



Citation: Peng, Y.; Ahmad, S.F.; Irshad, M.; Al-Razgan, M.; Ali, Y.A.; Awwad, E.M. Impact of Digitalization on Process Optimization and Decision-Making towards Sustainability: The Moderating Role of Environmental Regulation. *Sustainability* **2023**, *15*, 15156. <https://doi.org/10.3390/su152015156>

Academic Editors: Dragomir Mihai and Calin Gheorghe Dan Neamtu

Received: 3 September 2023

Revised: 2 October 2023

Accepted: 19 October 2023

Published: 23 October 2023



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1. Introduction

The manufacturing sector in Pakistan faces severe challenges due to the pervasive inefficiency in decision-making and the production process, which has powerful implications for sustainability [1]. Resource waste and increasing environmental effects result from old technology, poor automation, and inadequate oversight of supply chains [2]. The absence of data-driven decision-making, operations planning, and regulatory restrictions has limited sustainable and economic development [3]. These deficiencies negatively impact social and environmental well-being, reduce resource availability, and weaken economic viability [4]. To address this challenge, it is necessary to invest in technology, adopt sustainable practices, and make regulations to increase productivity, lessen environmental damage, and contribute to a greener manufacturing industry [5].

Digitalization has tremendously impacted manufacturing, the supply chain, health-care, energy, etc. Automation, data analytics, artificial intelligence, and the Internet of Things have reshaped processes, reducing waste and improving the quality of products and services [6]. The decision-making process is also changing concurrently due to predictive modeling and real-time data insights, which enable stakeholders to make decisions with significant sustainability outcomes [7]. Digital technology has reshaped traditional processes, advancing them to higher efficiency, adaptability, and ecological awareness and making businesses manage the complexity of a dynamic global marketplace [8]. The relationships between digitization, process optimization, decision-making, and sustainability have emerged as essential points to be explored in this era [9].

1.1. Problem Statement

Though digital technology can make decision-making based on data and process optimization possible, a comprehensive adoption of these developments into the sustainability framework is still a significant challenge [10]. There is a need to explore further the relationships among digitalization, process optimization, and decision-making toward sustainable practices [11]. Moreover, the urgent need to tackle sustainability issues necessitates an in-depth study of how combining digital technologies (DT), process optimization (PO), and decision-making (DM) frameworks may pave the way for sustainable development [12]. This study aims to fill this gap by providing findings regarding how digitalization can effectively obtain sustainability through process optimization and decision-making.

1.2. Research Objectives

The research has the following objectives:

1. This study examines digitalization's impact on process optimization and decision-making towards sustainable practices.
2. This research seeks to clarify how digital solutions may improve process efficiency and decision-making and create an enhanced approach to sustainability and social responsibility.

1.3. Research Significance

The research has a lot of significance for various industries, especially the manufacturing sector. Knowing how technology may improve efficiency, decrease waste, and assist decision-making is essential during increasing ecological issues and technological changes. It provides companies with practical insights to handle the complexity of digital transformation and align with sustainability goals by identifying the complex connections between DT, PO, DM, and sustainability. In addition, the results may encourage a paradigm shift, enabling firms to proactively resolve resource issues, reduce carbon emissions, and adopt novel strategies to promote economic development and sustainability.

2. Development of Theoretical Framework

2.1. Theories

The following theories provide the theoretical foundations for the research.

Digital Darwinism: This theory was presented by Brian Solis and focuses on how organizations must evolve and adapt in the age of digitization to survive and flourish [13]. It stresses how important it is to adopt digital technology and tactics to stay competitive in a corporate environment that is changing rapidly.

Lean Manufacturing: The concept is based on the Toyota Production System and focuses on minimizing waste and enhancing value in industrial processes [14]. It focuses on productivity growth, inefficiency elimination, and continuous improvement.

Rational Choice Theory: According to this theory, people evaluate multiple options and select the one that maximizes their use and advantages [15].

Sustainability Transition Theory: This theory underlines how innovation, reforms, and public pressure may lead to a transformation from unsustainable practices to sus-

tainable ones [16]. It acknowledges the contribution of laws, technology, and societal movements to the advancement of sustainability.

2.2. Digital Transformation of Manufacturing Industry

The manufacturing sector has long been renowned for focusing on machinery and physical processes [17]. However, the emergence of digital technology has brought about a significant change in how industrial processes are carried out [18]. This transition, often known as the “fourth industrial revolution,” entails incorporating digital technology into manufacturing-related processes. The Internet of Things (IoT) is one of several main forces behind this technological shift [19]. It has made the collection of real-time data and communication possible by connecting sensors, machines, etc., to the Internet; now, machines can communicate throughout the manufacturing process with each other [20]. The real-time data makes predictive and preventive maintenance possible, reducing fixing time, losses, and expenses [21]. Another core of this revolution is data analytics and artificial intelligence, which allows manufacturers to gather and analyze vast amounts of data generated at various stages of the production process [22]. This improves quality control while simultaneously optimizing processes. Early detection of faulty products reduces waste and enhances the quality of the product. The manufacturing sector’s DT is in line with sustainability [23]. Data analytics identifies areas to reduce waste and increase energy efficiency, supporting environmentally friendly processes [24]. The manufacturing sector’s DT has reshaped how products are produced, from enhanced efficiency in operations to better quality control and more environmentally friendly [25]. Despite the difficulties, there are enormous potential advantages, and companies that adopt DT will succeed within the current manufacturing landscape [26].

2.3. Digital Transformation and Process Optimization

DT has a significant role in PO, and firms use digital technology to improve and optimize their processes and operations [27]. Companies significantly increase efficiency and production by integrating digital technologies and procedures [28]. Firms reduce delays, lower mistakes, and speed up process completion by automating routine and manually performed tasks. For example, robotic process automation and other digital tools perform repetitive work, allowing humans to concentrate on complicated and strategic tasks [29]. This reduces process time and makes it consistent and accurate. Real-time analytics of data are another advantage of DT. Firms can gather and analyze data from multiple sources and gain useful knowledge about the processes. It also allows the firm to spot inefficiencies, problems, and weak areas by verifying key performance indicators and applying predictive analytics [30]. This helps firms make informed decisions, optimize the allocation of resources, and constantly improve processes [31]. In addition, DT makes cross-team and cross-department communication and collaboration easy through digital communication channels, project management systems, and cloud-based collaboration tools, leading to efficient processes, fewer delays, and enhanced coordination [32]. It is important to remember that DT calls for a comprehensive strategy considering organizational and technological factors. While deploying digital technologies is essential, businesses must also focus on staff training, handling disruptions, and cultural factors to successfully optimize their processes [33]. To successfully optimize processes via DT, involving people is essential, as is providing training and encouraging innovation and continual improvement [34].

In short, PO inside firms has been triggered by DT. Firms redesign processes, boost efficiency, and continually improve current processes by adopting automation, collaboration tools, real-time data analytics, etc. [35]. Adopting DT requires an adequate strategy considering organizational change and technological advances, ensuring PO [36].

2.4. Digital Transformation and Decision Making

DT has greatly influenced decision-making. The accessibility of real-time data are among the several primary advantages of DT [37]. Firms obtain and analyze data statistics

from various sources, such as client interactions, sales, operations, and market trends, and enable decision-makers to access real-time data and make better- and more-informed decisions [38]. Such decisions are more accurate and timelier regarding the situation of the company. Firms can also plan for upcoming opportunities or issues by updating themselves on market trends, customer demands, and key performance indicators [39]. Additionally, DT makes firms able to make data-driven decisions. Decision-makers use digital tools like machine learning algorithms and advanced analytics for analyzing massive data sets instead of merely relying on intuition or prior experience [40]. These technologies have unearthed obscure patterns and knowledge that traditional approaches would not observe. Firms can make more unbiased decisions using data-based facts [41]. DT also improves the decision-maker's ability to collaborate and communicate. Teams can collaborate realistically, exchanging data and ideas using digital platforms [42]. This encourages a process for making decisions that is more inclusive and considers various perspectives and expertise [43]. Digital technologies also make remote collaboration possible, enabling managers to communicate and act irrespective of their time zone and location [44]. DT also brought the opportunity for predictive analytics and scenario modeling. Before making decisions, managers can simulate multiple scenarios, evaluate potential results, and analyze different alternatives [45]. By lowering risk and uncertainty, this capability enables firms to make better decisions according to expected results [46].

It is crucial to remember that DT cannot replace the role of humans in decision-making [47]. Although data and analytics offer insightful information, human autonomy, wisdom, and intuition are still significant. A balance is still necessary between utilizing statistical information and stakeholder perspectives, contextual factors, and strategic goals for effective decision-making [48].

2.5. Moderating the Role of Environmental Regulation on Process Optimization toward Sustainability

Governments and many other national and international organizations make environmental regulations (EnR) that guide businesses and industries to lessen the negative impact of their processes and ensure sustainability [49]. EnR is essential in directing and influencing how firms design and enhance their operations to reduce environmental impact [50]. Such regulations establish carbon footprint and waste reduction requirements and push the firm to optimize its processes [51]. Some examples are using cleaner technology, increasing combustion efficiency, and using alternative energy sources [52]. EnR supports the efficient utilization of resources by establishing guidelines and objectives for utilizing resources. Firms need process optimization to reduce the use of resources, including raw materials, electricity, and water, which is achieved by improving processes, adopting efficient machinery, or recycling resources [53]. EnR pushes firms to optimize their operations to reduce waste production, separate waste streams, and make recycling and appropriate disposal easier [54]. This includes implementing waste reduction efforts, enhancing waste segregation techniques, or working with recycling facilities. EnR also requires compliance and reporting according to process metrics to ensure its implementation [55]. EnRs are also necessary to promote teamwork and implement modern approaches to process optimization [56]. To develop and implement process optimization plans, firms must work collaboratively with technology manufacturers, industry peers, and regulatory institutions [57].

In conclusion, EnR is moderating the relationship between process optimization and sustainability. It drives firms to comply with procedures, enhance resource efficiency, use better waste management and recycling techniques, and promote innovation and collaboration. Firms can optimize their processes to reduce their environmental impact, increase productivity, and create a more sustainable future by adhering to these standards [58].

2.6. Moderating the Role of Environmental Regulation on Decision-Making towards Sustainability

EnRs are essential for directing firms to consider environment-related factors when making decisions and provide legal guidelines that must be followed [59]. These rules set acceptable limits for waste disposal, CO₂ emissions, resource usage, and other ecological factors. Firms consider these regulatory requirements while making decisions to assure compliance [60]. EnR influences decision-making by requiring firms to evaluate the long-term repercussions of their activities for sustainability and match their choices with the standards [61]. EnR requires firms to perform risk analyses and reduce environmental adverse effects. Firms consider their choices' possible environmental hazards and effects while making decisions [62]. This involves assessing the effects on biodiversity, air, water, etc. It drives firms to prioritize sustainability factors when making decisions and makes them responsible for their ecological footprint and disclosure [63]. Additionally, it enforces stakeholder participation in the process of decision-making. Decisions having an environmental impact must be made after the consultation of environmental institutions, local communities, and regulatory agencies to reduce the environmental impact and ensure sustainability [64].

These rules obligate firms to develop environmentally friendly options when they make decisions. Such practices are severely required to achieve sustainability objectives and reduce environmental effects [65]. Firms are also forced to explore and implement technologies, procedures, and strategies to reduce resource use, decrease emissions, and advance the principles of a circular economy [66]. Decision-makers are also prompted to look for sustainable alternatives with more extended environmental benefits [67]. In a nutshell, environmental rules moderate managerial decisions for sustainability. By establishing legislative standards, encouraging risk evaluation and reduction, requiring reporting on sustainability, supporting input from stakeholders, and fostering innovation, EnR influences the decision-making process for sustainability. Firms can make better decisions that protect the environment by following these standards [68].

2.7. Sustainability

The rapidly changing environment of today has made sustainability an important topic with resonance in various industries and societies [69]. Sustainability is fundamentally about exercising appropriate stewardship and making sure that the resources and wellbeing of future generations are not jeopardized by our activities [70]. It is a theory that balances human and social equity, economic growth, and the preservation of the environment. Achieving sustainability is not without hardships. Between these dimensions, trade-offs frequently occur [71]. For instance, shifting to clean energy sources could necessitate significant initial expenses. Many industries, like fossil fuels, provide an example of how difficult it may be to achieve a balance between economic growth and environmental preservation [72]. In other words, if we focus on the development of one dimension, the other three will be impacted, and most probably negatively. In order to achieve sustainability, different stakeholders must work together [73]. Governments, companies, NGOs, and people all have important responsibilities to play. To encourage sustainable practices, laws and policies must be enacted. Businesses are required to consider social and environmental factors in their plans, and people have to make conscious decisions every day [74].

Moving forward, changes in cultural values, legislation, and technology improvements are expected to influence the course of sustainability. For instance, new technologies like blockchain and AI indicate potential for improving various business activities and supporting sustainable processes. The policies aimed at reducing emissions and advancing sustainable energy also need to be changed accordingly. Sustainability is essentially an ongoing process. It is a commitment to continuous improvement rather than a goal that can be accomplished. It is a recognition of our joint responsibility for the planet's and people's wellbeing. By taking essential action, we can all contribute to a more sustainable future.

Sustainability is a modern term that modern social scientists use to preserve the future and current environment [75]. Sustainability means using existing natural resources to balance the environment [76]. Sustainability also refers to continuously maintaining or supporting a process over time [77]. It is to meet the needs of the present generations without sacrificing the ability of the future generations to meet their own needs, and it is currently the most researchable topic among social scientist researchers [78]. Different factors are responsible for a business's sustainability, but industrial digitalization is one of them. A business cannot convert its processes to sustainable ones without considering digital technology [79]. Digital technology is spreading at a high speed among global industries. Digitalization is a new trend that reduces the industry's costs and increases efficiency in doing things [80]. Paperwork is the major use of industries and other organizations for office use and documentation. As we know, paper is created by plants, which are natural resources that have a significant role [81]. As industries move more towards digitization, their paper usage will also reduce gradually, reducing the cutting of trees to protect the environment [82].

2.8. Theoretical Mechanism, Framework

The framework of the research is derived from the theories of Digital Darwinism, Rational Choice Theory, Lean Manufacturing, and Sustainability Transition Theory. Digitalization speeds up the implementation of lean principles, improves decision-making, and assists in the shift toward sustainability [83]. Firms can develop more efficient and sustainable processes and informed choices via these theories in the context of digitalization [84].

2.8.1. Digital Darwinism (DD)

The DD emphasizes how important it is for businesses to evolve and adapt in the digital era. The framework suggests that sectors that adopt DT have an edge in streamlining procedures and adopting choices that advance sustainability [85]. Digital technologies make it possible to collect, analyze, and communicate data in real-time, which enables firms to quickly spot inefficiencies and sustainability gaps [86]. Firms that do not embrace DT face the risk of falling behind and losing opportunities for enhancing their decision-making and processes for sustainability.

2.8.2. Lean Manufacturing Theory (LMT)

The LM focuses on reducing waste and improving value. Digitalization serves as an engine for implementing lean concepts [87]. With the help of digital technologies like IoT, blockchain, and data analytics, firms can monitor various processes in real-time, spot bottlenecks, minimize downtime, and allocate resources more efficiently. Through the use of data-driven decisions, processes may be optimized and resource efficiency increased, subsequently advancing sustainability by reducing resource use and waste [88].

2.8.3. Rational Choice Theory (RCT)

According to the RCT, people make decisions in an effort to maximize their utility and advantages [89]. According to the framework, digitization gives decision-makers improved access to data and insights, enabling them to make more informed and logical decisions. Real-time data about consumption of resources, process efficiency, and ecological effects is provided via digital technologies [90]. This gives decision-makers the power to evaluate the benefits and long-term effects of their decisions on sustainability.

2.8.4. Sustainability Transition Theory (STT)

The STT emphasizes how innovation, institutional reform, and social pressure lead to a move from unsustainable acts to sustainable ones [91]. Digitalization is a key factor in this transformation, according to the framework. Digital technologies encourage accountability and transparency by making it possible to track and control measures of sustainability [92]. Firms that adapt to sustainable transitions by using digital technology

for the optimization of processes and decision-making contribute to driving society more broadly towards sustainability.

2.8.5. Theoretical Mechanism

The combination of DD, LM, RCT, and SST demonstrates how the PO and DM processes, which are all intended to promote sustainability, are strongly impacted by digitalization. Businesses are pushed to adopt digital tools by the theory of DD, which is shifting to a new digital era [93]. As a result, data can now be collected and analyzed in real-time, immediately informing and improving decision-making. Similarly, by embracing the concepts of LM, digitalization makes it easier to identify inefficiencies and inefficient behavior through analysis of data, improving the effectiveness of processes [94]. In addition, RCT becomes relevant as accurate data becomes more readily available and decision-makers are given the tools to make informed decisions that balance short-term benefits with long-term sustainability [95]. In the end, this comprehensive integration confirms the STT, since accountability and transparency brought by digitalization drive industries towards more sustainable practices. Together, these elements provide a holistic framework that uses digitization as an engine to promote efficient, informed, and sustainable operations in manufacturing industries. The theoretical framework and hypotheses shown in Figure 1 are based on this mechanism.

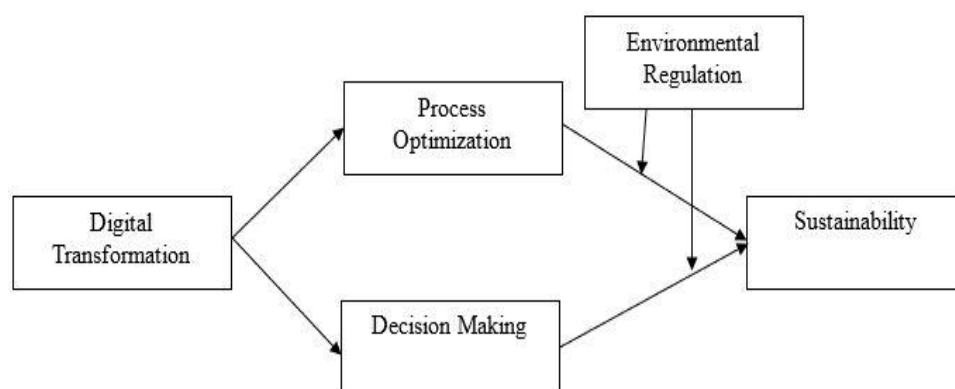


Figure 1. Theoretical Framework.

2.9. Hypotheses

H₁. Digital transformation has a significant impact on process optimization.

H₂. Digital transformation has a significant impact on decision-making.

H₃. Process optimization has a significant impact on sustainability.

H₄. Decision-making has a significant impact on sustainability.

H₅. Environmental regulations moderate the effect of process optimization on sustainability.

H₆. Environmental regulations moderate the effect of decision-making on sustainability.

3. Materials and Methods

3.1. Research Design and Philosophy

Research philosophy is the key driver that guides the researcher at every step of the research [96]. Two major philosophies common among social science researchers are positivism and interpretivism [97]. This study derives its roots from the positivist philosophy. The positivism paradigm is based on absolute scientific beliefs that rely on

a single measurable, quantifiable reality [98]. Due to quantifiable reality, a quantitative methodology will better address the issue in question with an approach of deduction.

3.2. Methods

Among the different methods used in quantitative research, a survey-based method was used for this study. A survey was used to collect data from the research respondents. The respondents of this study were the managerial-level employees of the manufacturing sector in Pakistan. A closed-ended questionnaire was used to collect the data from the 650 respondents using a sampling approach based on purposive sampling from the overall population of the manufacturing sector. Further, the analysis of the gathered data were conducted by structural equation-based modeling via SmartPLS.

3.3. Instrument

The research survey instrument for this study was based on three sections. The first section reflects the respondent's consent. The second section is based on demographic questions, and the last section consists of questions based on the measures of this study constructs. Five constructs were adopted from the prior studies, considering the scales' reliability and validity. All the constructs' items were measured on a five-point Likert scale, where 1 denotes the lowest level of agreement and 5 denotes the highest level. A list of all the constructs with their respective items and sources of adoption is given below in the Table 1.

Table 1. Measurement Instrument.

Construct	Items
Digital Transformation [99]	The Internet service is available all the time. The cost of the internet connection is reasonable for my household. The Internet enables me to accomplish my tasks more quickly. The Internet helps me find new opportunities (e.g., employment, education, and business). The Internet helps me learn and develop new skills and knowledge. The Internet has had a positive impact on my work performance. Internet use has become an everyday part of my life. The Internet helps me connect with community, social, or sporting groups.
Process Optimization [100]	The company's manufacturing process effectively reduces the emission of hazardous substances or waste. The manufacturing process of the company recycles waste and emissions that allow them to be treated and re-used. The manufacturing process of the company reduces the consumption of water, electricity, coal, or oil. The manufacturing process of the company reduces the use of raw materials.
Decision Making [101]	How easy or difficult was the process of trying to find an answer? I believe there is a good match between my decision and the decision to support technology. I believe the decision support technology is not well suited for my decision. I believe there is an excellent fit between my decision and the decision support technology. I believe there is a mismatch between my decision and the decision to support technology.
Environmental Regulation [102]	The government provides easy-to-understand information on environmental issues. The government provides information on environmental issues in languages spoken by significant population segments. Regulations on environmental issues are published on time. Local environmental issues and regulations are published on time. Environmental administrative proceedings at the local level are conducted without unreasonable delay. Environmental regulations are sufficiently stable to permit the public to ascertain what conducts are permitted and prohibited.
Sustainability [103]	We actively monitor water usage in our facilities. We actively monitor energy usage in our facilities. We implement a systematic approach to setting environmental targets. We implement a systematic approach to achieving environmental targets. We actively monitor water usage in our facilities. We actively monitor energy usage in our facilities.

4. Results and Data Analysis

4.1. Demographic Statistics

Table 2 of the demographic statistics shows the demographic distribution of the research respondents. The first section of the table shows the gender-wise distribution of the respondents, which shows that among the 554 respondents, 70.8% are male and 29.2% are female. The second section represents the age-wise distribution of the respondents, which shows that among the 554 respondents, the majority belongs to the age group of 20 to 30 years, with a percentage of 42%, with the highest number of respondents, while the age group of 51 and above years shows the lowest level of respondents with a percentage of 12%. The table's third and last section denotes the respondents' relevant industry experience. This section shows that based on experience, respondents are divided into four groups, i.e., less than one year, 1 to 5 years, 5 to 10 years, and more than ten years. Table denotes that most respondents belong to 1-5 years of experience with a percentage of 46%, while those with less than 1-year experience have the least number with a percentage of 12%.

Table 2. Demographic Statistics.

Gender	Frequency	Percentage
Male	392	70.8%
Female	162	29.2%
Total	554	100.0%
Age Group	Frequency	Percentage
20 to 30 Years	233	42%
31 to 40 Years	134	24%
41 to 50 Years	120	22%
51 and Above Years	67	12%
Total	554	100%
Industry Experience	Frequency	Percentage
Less than 1 Year	68	12%
1 Year to 5 Years	255	46%
5 to 10 Years	123	22%
More than 10 Years	108	19%
Total	554	100%

4.2. Assessment of the Measurement Model

4.2.1. Reliability of the Scales

Reliability refers to the accuracy of measurement results and calculations [104]. Using an approach based on partial least squares, there are two basic types of reliability: named items and construct reliability. The measure used for the item's reliability is outer loading, while the measure used for the construct's reliability is Cronbach alpha and composite reliability [105]. The threshold value for both reliability measures is 0.7 or above, but, in some cases, even a value of 0.6 is also acceptable if the initial criteria of reliability and validity are established [106]. Table 3 shows that all the constructs and their respective items have a reliability value greater than the threshold value, indicating that all the constructs and their respective items are reliable for further study.

4.2.2. Convergent Validity of the Scales

Convergent validity refers to how much the items of a construct are related to each other [107]. The measure used for convergent validity is Average Variance Extracted (AVE). The threshold value for the AVE is 0.5 or above, but in some cases, even a value of 0.4 is acceptable if the initial criteria of items and construct reliability are met [108]. Table 4 below of the convergent validity shows that all the constructs have AVE values greater than the threshold value, indicating that all the constructs are convergently valid.

Table 3. Reliability of the Scales.

Construct	Items	Outer Loadings	Cronbach Alpha	Composite Reliability
Decision Making	DM2	0.780	0.781	0.859
	DM3	0.708		
	DM4	0.827		
	DM5	0.789		
Digital Transformation	DT1	0.710	0.833	0.876
	DT2	0.710		
	DT3	0.718		
	DT4	0.716		
	DT5	0.770		
	DT8	0.784		
Environmental Regulation	ER2	0.816	0.866	0.903
	ER3	0.844		
	ER4	0.775		
	ER5	0.802		
	ER6	0.797		
Process Optimization	PO1	0.827	0.845	0.896
	PO2	0.840		
	PO3	0.838		
	PO4	0.799		
Sustainability	SB1	0.663	0.891	0.917
	SB2	0.848		
	SB3	0.858		
	SB4	0.812		
	SB5	0.847		
	SB6	0.791		

Note: ER2, DT6, DT7, and DM1 were removed from the model due to insignificant outer loadings.

Table 4. Convergent Validity of the Scales.

Construct	AVE
Decision Making	0.604
Digital Transformation	0.540
Environmental Regulation	0.651
Process Optimization	0.683
Sustainability	0.650

4.2.3. Discriminant Validity of the Scales

Discriminant validity refers to how one construct of a research model is theoretically different from the other construct of the same model [109]. Several measures are used for discriminant validity, but the most common are the Fornell-Larcker criteria, HTMT values, and cross-loadings [110]. According to the researchers and statisticians, a model based on the partial least squares technique regressed by the SmartPLS Fornell-Larcker criteria and HTMT values is recommended [111].

Fornell Larcker criteria: Fornell-Larcker criteria are one of the most robust techniques in the SmartPLS to diagnose the discriminant validity issue in the model [112]. The measure used for the Fornell Larcker criteria is the square of the AVEs, which are diagonal values in the Fornell Larcker table. Researchers suggest that the diagonal values must be greater than the values of their corresponding rows and columns for the threshold value of discriminant validity [113]. Table 5 denotes that all the diagonal values are more significant than the values of its columns and rows, which indicates that all the model constructs are discriminately valid.

Table 5. Fornell Larcker Criteria.

	DM	DT	ER	PO	SB
Decision Making	0.777				
Digital Transformation	0.075	0.735			
Environmental Regulation	0.449	0.232	0.807		
Process Optimization	0.286	0.183	0.411	0.826	
Sustainability	0.441	0.301	0.464	0.508	0.806

HTMT values: HTMT stands for Heterotrait-Monotrait, which is another robust technique in the SmartPLS for diagnosing discriminant validity. The threshold value for the HTMT values is that all the HTMT values must be smaller than 0.85 [114]. Table 6 shows that all the HTMT values are lower than the threshold values, which indicates that all the constructs present in the model of this study are discriminately valid.

Table 6. HTMT.

	DM	DT	ER	PO
Digital Transformation	0.127			
Environmental Regulation	0.535	0.263		
Process Optimization	0.349	0.204	0.477	
Sustainability	0.522	0.341	0.516	0.574

4.3. Assessment of the Structural Model

4.3.1. Common Method Bias

Common method bias is a common issue in primary data research where the data for the independent and dependent variables are collected from the same respondent [115]. There are several measures to diagnose this issue, but the statisticians and researchers, when using SmartPLS, suggest that Variance Inflated Factors (VIF) are the most robust measure to detect the common method bias [116]. According to them, if the VIF values are equal to or less than 3.3, then it is considered that the model is free from the issue of common method bias. Table 7 shows that all the items presented in the model have VIF values smaller than the threshold values, which indicates that the model is free from the issue of common method bias.

4.3.2. Structural Model

Figure 2 exhibits the relationships among this study variables.

4.3.3. Model Fitness

Once the reliability and validity of the scales are achieved, it is recommended to confirm the fitness of a model before regressing it. Model fitness is an advanced measure in the SmartPLS to estimate how well this study model fits. Several measures are used for model fitness, like SRMR, Chi-Square, NFI, etc. Statisticians suggest SRMR is the most robust measure for model fitness when using a variance-based approach to primary data [117]. The threshold value for the model fitness for the SRMR is 0.08 or below. Table 8 indicates that the SRMR value for the saturated model is 0.064, indicating that the model is fit to be regressed further for the analysis.

4.3.4. Hypothesis Testing (Direct Relationships)

Regression analysis is a very old technique researchers and statisticians use to diagnose a cause-and-effect relationship between two or more variables [118]. The measures used for the statistically significant relationship based on regression are t and p values. The threshold value for the p-value is 0.05 or less, and the threshold value for the t-value is 1.96 or above [119]. The table of hypothesis testing based on direct relationships shows a total of four hypotheses for this study. Table 9 shows that all four direct relationship-based hypotheses have a p-value

smaller and a t-value greater than the threshold value, which indicates that the findings of this study support all four direct relationship hypotheses based on this study, while the beta value for each relationship describes the strength of that relationship.

Table 7. Multi-collinearity statistics.

Items	VIF
DM2	1.569
DM3	1.387
DM4	1.848
DM5	1.811
DT1	1.490
DT2	1.593
DT3	1.703
DT4	1.740
DT5	1.776
DT8	1.583
ER2	2.305
ER3	2.607
ER4	1.690
ER5	1.983
ER6	1.792
PO1	1.928
PO2	2.053
PO3	1.961
PO4	1.742
SB1	1.465
SB2	2.573
SB3	2.848
SB4	2.406
SB5	2.836
SB6	2.124

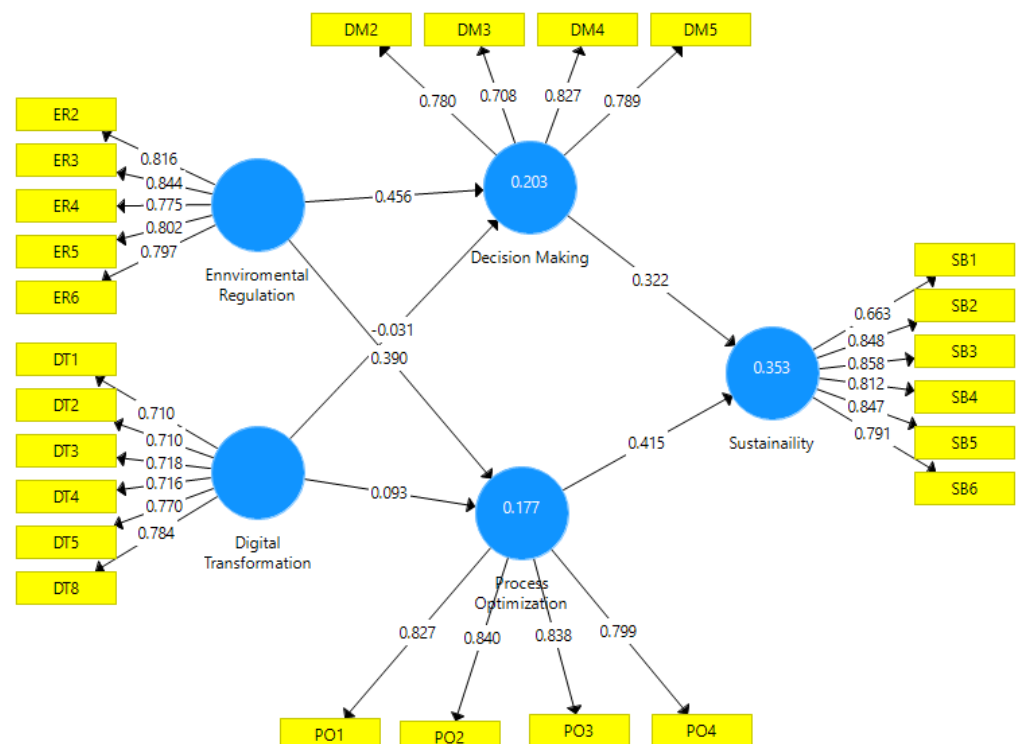


Figure 2. Structural Model.

Table 8. Model Fitness.

	Saturated Model	Estimated Model
SRMR	0.064	0.081
d_ULS	1.337	2.115
d_G	0.454	0.479
Chi-Square	1705.312	1737.511
NFI	0.796	0.792

Table 9. Hypothesis Testing (Direct relationships).

Hypothesis	β	T Statistics	p Values	Results
H1. Digital Transformation $\rightarrow$ Process Optimization	0.093	2.621	0.005	Supported
H2. Digital Transformation $\rightarrow$ Decision Making	0.150	7.174	0.000	Supported
H3. Process Optimization $\rightarrow$ Sustainability	0.415	9.803	0.000	Supported
H4. Decision Making $\rightarrow$ Sustainability	0.322	10.252	0.000	Supported

4.3.5. Hypothesis Testing (Moderating Relationships)

Table 10 shows the statistics of moderating relationships. Both are based on the moderating effect of environmental regulations on the relationship between process optimization and decision-making towards sustainability. The table shows that both moderating relationship-based hypotheses have a *p*-value smaller and a *t*-value greater than the threshold value, which indicates that the findings of this study support both moderating relationship hypotheses based on this study, while the beta value for each relationship describes the strength of that relationship.

Table 10. Hypothesis Testing (moderating relationships).

Hypothesis	β	T Statistics	p Values	Results
H5. ER $\times$ PO $\rightarrow$ Sustainability	0.183	6.112	0.000	Supported
H6. ER $\times$ DM $\rightarrow$ Sustainability	0.130	2.778	0.003	Supported

4.3.6. R Square

R square, also known as the coefficient of determination, refers to the percentage of variation in the dependent variable due to the collective effect of the independent variables [120]. Table 11 shows an R square value of 0.353, which denotes that 35.3% of the variation in the dependent variable sustainability is due to process optimization, decision-making, and environmental regulation.

Table 11. R Square.

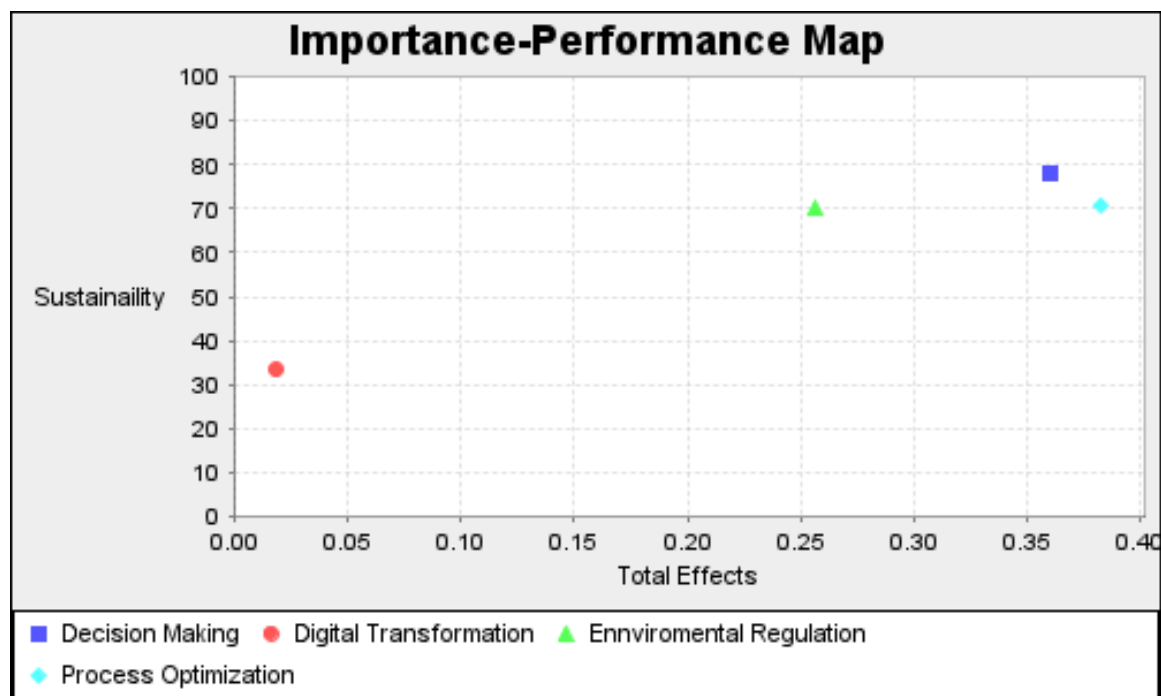
	R Square	R Square Adjusted
Sustainability	0.353	0.351

4.4. IPMA Analysis

IPMA stands for Importance and Performance Matrix Analysis. It is an advanced test used in the SmartPLS, which describes the importance and performance of the individual variables for the target variable sustainability in the context of the said research model [121]. Table 12 shows that process optimization has the highest importance value of 38.2%, while decision-making, with a value of 78.15%, is the highest performed value. Figure 3 denotes the graphical representation of these values.

Table 12. IPMA Analysis.

Sustainability	Importance	Performances
Decision Making	0.360	78.152
Digital Transformation	0.018	33.399
Environmental Regulation	0.256	70.442
Process Optimization	0.382	70.838

**Figure 3.** IPMA Analysis.

4.5. Predictive Power of Accuracy

The predictive power of accuracy explains the prediction power of the model when tested in a different context. The model's predictive relevance measure is called Q square [122]. According to the researcher, a model with a Q square value greater than zero is considered a good model and reliable to predict in a different context [123]. Table 13 of the Q Square indicates a value of 0.22 for the dependent variable sustainability, which shows that the model has a prediction power of 22%.

Table 13. Q Square.

	SSO	SSE	Q ² (=1 – SSE/SSO)
Decision Making	2600	2264.67	0.129
Digital Transformation	3900	3900	
ER/DT/DM	650	650	
ER/DT/PO	650	650	
Environmental Regulation	3250	3250	0.118
Process Optimization	2600	2292.24	
Sustainability	3900	3040.86	0.22

4.6. MGA Analysis

MGA stands for multi-group analysis. It is an advanced test used in the SmartPLS to compare the two population groups within the research sample and how the relationship of the study is affected due to the presence or absence of that group [124]. Table 14 below shows the gender-wise comparison of the MGA analysis. The measure used for statistical

significance is the p -value. The threshold value for statistical significance is 0.05 or below. The table of MGA shows that all the relationships have a p -value smaller than the threshold value, indicating no significant impact on this study relationship due to gender.

Table 14. MGA Analysis.

Relationships	β -Diff (Male-Female)	p -Value
Decision Making $\rightarrow$ Sustainability	−0.111	0.06
Digital Transformation $\rightarrow$ Decision Making	−0.044	0.354
Digital Transformation $\rightarrow$ Process Optimization	0.081	0.173
ER/DT/DM $\rightarrow$ Decision Making	−0.16	0.093
ER/DT/PO $\rightarrow$ Process Optimization	0.058	0.281
Process Optimization $\rightarrow$ Sustainability	0.064	0.242

5. Discussion

The conceptual framework of this study contributes knowledge. The framework has digital transformation as an independent variable, having an effect on sustainability as a dependent variable; process optimization and decision-making as mediators; and environmental regulation as a moderator. This study aims to examine the impact of digital transformation on sustainable development practices in the manufacturing sector of Pakistan. This study further aims at how digital transformation initially impacts industry process optimization and decision-making processes, which will eventually lead the industry towards sustainability, and how the environmental regulations imposed by the regulatory authorities will boost this process more efficiently. Based on this model, a study has driven six hypotheses, among which four are based on direct relationships and two are based on moderating relationships. Direct hypotheses are based on relationships between digital transformation to process optimization, digital transformation to decision-making, process optimization to sustainability, and decision-making to sustainability. Both indirect relationships based on the moderating effect of environmental regulations are based on the relationships of digital transformation to process optimization and digital transformation to decision-making.

The first hypothesis argues that digital transformation will lead the manufacturing sector of Pakistan toward better process optimization. This study's results also support the hypothesis that digital transformation in the manufacturing sector of Pakistan will optimize processes, with a p -value of 0.005 and a beta value of 0.093. Literature and results based on the prior studies conducted on the same relationship in a different industry and geographical context also indicate the same findings: if industrial processes are shifted from manual to digital, it will lead the industry toward better process optimization [125,126]. The second hypothesis is based on the relationships that show that digital transformation in the manufacturing sector of Pakistani industries will significantly impact their decision-making. However, the results based on the empirical evidence of this study also support the same argument that if the manufacturing sector of the Pakistani industry is shifted from a manual system to a digital system, it will significantly impact their decision-making in a positive context, with a p -value of 0.000 and a beta value of 0.150. Prior studies based on the same relationships, although conducted in different contextual and geographical scenarios, also had findings aligned with the results of this study [127,128].

The third hypothesis claims that after the implementation of the digital transformation in the industry, the processes of the industry get optimized, and later, due to these optimized processes, the industry will lead toward the industry's sustainable practices [129,130]. The empirical results based on this study's data analysis also support the argument that better-optimized processes in the manufacturing industry will move the industry towards better sustainable practices, with a p -value of 0.415 and a beta value of 0.000. Different researchers from different geographical contexts also show the same findings aligned with the results of this study. Based on the direct relationships, the fourth and last hypothesis claimed

that implementing digital transformation in the industry would lead to better decision-making [131]. Eventually, this better decision-making will lead the manufacturing sector of Pakistan towards better and more efficient sustainable practices. However, the empirical findings of this study also support the argument that better decision-making will lead to better and more efficient sustainable practices, with a p -value of 0.000 and a beta of 0.322.

The fifth and sixth hypotheses are the moderating hypotheses. The moderating variable for both hypotheses is environmental regulations. The fifth hypothesis claimed that when environmental regulations are increased upon the industry by the authorities, it will lead to a better digital transformation to optimize the processes when there is no regulation [132]. The sixth and last hypothesis claimed by this study argues that when environmental regulations by the authorities are increased, this will lead firms towards better decision-making due to the digital transformation. However, from the empirical findings of this study, it was determined that the results are also aligned with both hypotheses, with p values of 0.000 and 0.003 and beta values of 0.183 and 0.130, respectively. However, the prior studies also support this argument that any regulation or rule imposed by the regulatory authority on the industry has a significant positive impact on the industry, moving it towards the practice that the regulatory authority was going to impose as compared to no regulatory action [133,134]. By encouraging PO and informed DM, digitization is essential for advancing sustainability. Utilizing technology, businesses will improve efficiency, use fewer resources, and produce less waste, all of which contribute to a more sustainable future [135], but it must be according to EnR [136]. Digitization enables firms and governments to take well-informed decisions that prioritize sustainable development through data-driven insights and real-time monitoring [137]. It improves operational effectiveness while also making it possible to embrace environmentally responsible practices, eventually leading to a sustainable world.

5.1. Contribution to Sustainable Development Goals (SDGs)

However, this study indirectly contributes to the overall sustainable development goals of the United Nations by 2030, but it highly impacts SDG9, SDG11, SDG12, and SDG13.

1. SDG9 states that investment in the infrastructure of the industry and its innovation is a significant driver to move that industry towards economic growth [138]. This study is based on the industry's sustainable development and how digitalization will impact it. As we know, for the digital transformation of the industry, it is necessary that the industry be supportive of innovation, and its infrastructure must also be supportive of adopting digital technology. If the industry is going to upgrade into digital transformation, it must ensure its structure and infrastructure.
2. SDG11 argues that half of the world's population currently lives in cities. According to their estimation based on past data and future technology development, in 2050, this ratio will be upgraded, and it is estimated that two-thirds of the world's population will move to cities and urban areas [139]. As we know, most industries are also located in the main cities of any country. Due to the rapid growth of cities due to mass migrations, cities must develop sustainable communities. So, the upgradation of the industry towards sustainable practices is also a part of developing a sustainable community in the industry, which will indirectly affect the sustainability of the city where the industry is located.
3. SDG12 argues that to achieve sustainable development and an economically grown society, we must change how we produce and consume goods and resources [140]. This study will transform the entire industry process to digitalize it, leading the industry to a sustainable organization.
4. SDG13 states that the planet's climate has been drastically affected recently. According to them, since 1990, greenhouse gases, which are the key elements responsible for climate change, have increased by 50 percent [141]. This study will motivate industries to transform their total industry processes into green processes to reduce greenhouse gases and other negative environmental effects and make them sustainable organizations.

5.2. Conclusions

This study examines how digital transformation will enable Pakistan's manufacturing industry to work better on sustainable practices. This study also aims to determine how digital transformation will affect the process optimization and decision-making of the manufacturing industry in Pakistan and how these practices will lead the industry to a sustainable industry in the long term. This study also aims to determine the role of environmental regulations during these complete processes. However, the empirical findings of this study also support all these arguments about when the industry will transform towards digitalization. In the first stage, it will better optimize its processes and decision-making, and then, as a result of this better process optimization and decision-making, it will move the industry towards sustainability. Results also found that when environmental regulations are imposed on the industry, it will provoke this process toward sustainable practices. In conclusion, this study will help the manufacturing industry transform into digitalization to make their industry on the list of sustainable organizations.

5.3. Implications

5.3.1. Theoretical Implications

This study provides a significant theoretical framework for manufacturing and other industries to transform themselves into digital organizations that are sustainable. This novel theoretical framework also adds to the body of knowledge on the impact of environmental regulation. This study adds to how regulations imposed by a particular regulatory organization impact the adoption of digitalization and the practice of sustainable practices. Further researchers can replicate the same theoretical model in different industries to examine that specific industry behavior regarding digitalization and sustainability.

5.3.2. Practical Implications

This study also offers different practical consequences for the body of knowledge. This study will help the people in the industry involved in the industry's decision-making process related to digitalization and sustainability. This study will also provide a roadmap to the managers in the manufacturing and other related sectors of Pakistan and globally on implementing digitalization in the organization. It will also guide them on how digitalization is channeled through different channels and will result in the industry's sustainability. The findings of this study also suggest how the regulation policies related to the environment by the regulatory authorities will affect the industry and their role in digital transformation.

5.3.3. Policy Implications

This study also offers several policy implications for industry regulatory authorities, government regulatory authorities, and other national and international agencies. This study suggests that the government regulatory authorities should have proper rules and legal processes for environmental regulations to implement digitalization properly in manufacturing and other industries and initiate sustainable practices better. The organization should create its own regulatory body for environmental protection practices and avoid the industry sustainably.

5.4. Limitations and Potential Areas of Future Studies

Limitations are the gaps a study leaves, and they provide directions for future researchers to fill these gaps. There are several limitations to this study. Firstly, this study was only conducted in the manufacturing sector of Pakistan. So, that is why we cannot generalize this study's findings to Pakistan's overall industrial sector. That is why it is recommended that future researchers test the same model in different industrial contexts to increase the generalizability of the findings of this study. Further, this study was only based on a quantitative approach, where the researcher adopted a model based on prior established theories. However, over time, several limitations will arise for the theory. It is recommended that the researcher conduct a qualitative study on the same topic to explore

new bridging channels that provoke the relationship between digital transformation and sustainability.

Furthermore, the influence of cultural and social factors also remained outside of this research's scope, which is one of its limitations. Future work is necessary on their impact on digitalization. Last but not least, research is necessary for the steps and preparation required for successful digitalization.

Author Contributions: Conceptualization, S.F.A. and Y.P.; methodology, M.I. and M.A.-R.; software, Y.A.A. and E.M.A.; validation, S.F.A. and M.I.; formal analysis, S.F.A.; investigation, M.I.; resources, S.F.A.; data curation, M.I.; writing—original draft preparation, S.F.A., M.I., M.A.-R., Y.P., Y.A.A. and E.M.A. writing—review and editing, M.I.; visualization, S.F.A.; supervision, S.F.A. and Y.P.; project administration, S.F.A.; funding acquisition, Y.P. and M.I. All authors have read and agreed to the published version of the manuscript.

Funding: The authors present their appreciation to King Saud University for funding this research through Researchers Supporting Program number (RSP2023R206), King Saud University, Riyadh, Saudi Arabia.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: Data will be available by requesting the corresponding author.

Acknowledgments: The authors also present their appreciation to Huazhong University of Science and Technology China, Institute of Business Management Pakistan, King Saud University, Saudi Arabia and University of Gwadar for their support during the research.

Conflicts of Interest: The authors declare no conflict of interest.

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