

Biostatistical and Digital Capabilities for Green Competitive Advantage: Evidence from Data Driven and Green Decision-Making Quality

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ABSTRACT

Pharmaceutical organizations face increasing pressure to achieve environmental sustainability and competitive advantage while managing growing amounts of organizational and environmental data. However, limited research has examined how biostatistical capabilities and digital technology can strengthen data driven decision making and subsequently improve green decision-making quality and green competitive advantage. Therefore, this study examines the effects of biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology on data driven decision making, and further investigates the effects of data driven decision making on green decision-making quality and green competitive advantage. We used a quantitative, cross-sectional research design. Data were collected from employees of pharmaceutical-sector organizations through a self-administered questionnaire. Of 450 distributed questionnaires, 300 valid responses were obtained. Convenience sampling was used, and the data were analyzed using Structural Equation Modeling (SEM). The results show that biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology have significant positive effects on data driven decision making. Data-driven decision-making significantly influences green decision-making quality, while green decision-making quality significantly contributes to green competitive advantage. The findings suggest that pharmaceutical organizations can strengthen their green competitive advantage by developing employee's biostatistical knowledge and training, fostering positive attitudes toward statistical evidence, strengthening biostatistical research capabilities, and investing in digital technologies that support data-driven and environmentally responsible decision-making.

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1. Introduction

In the current dynamic environment, companies face challenges relevant to gaining competitive advantage due to growing environmental pressures, resource constraints, sustainability expectations, and technological changes (Widyantoro et al., 2025). Due to this, green competitive advantage (GCA) has become an integral strategic outcome for the companies seeking to differentiate themselves through environmentally responsible products, processes, technologies, and practices (Rahayu et al., 2023). GCA could be considered an effective ability of the companies for obtaining competitive benefits through environmental capabilities, green products, green processes, ecological innovation, and effective environmental strategies (Liou et al., 2021). From the natural-resource-based view, Hart (1995) argued that environmental capabilities can become strategic resources that enable firms to achieve competitive advantage by developing capabilities related to pollution prevention, product stewardship, and sustainable development. In this regards, companies which are being successfully developed a environment friendly products and also able to implement the green technology then they could achieve their competitive position (Muisyo et al., 2022). Various factors improve the competitive advantage of companies. Among those, Shehzad et al. (2024) demonstrated the importance of green innovation and green core competence for achieving competitive advantage, while Ge et al. (2018) found that green innovation strategy can contribute to sustainable competitive advantages. In the same vein, green innovation is also being identified an integral mechanism where business analytics and environmental orientation could contribute to GCA (Zameer et al., 2022). Other recent study also highlighted that quality of organizational green decision making significantly increase the green competitive advantage of the

organization (Muisyo et al., 2022). Keeping in view previous studies, understanding the organizational factors that enable firms to develop green competitive advantage is an important area of research.

Green decision-making quality becomes an important factor to improve the GCA. Green decision making quality is being referred to the extent where environmental decisions are based on relevant, reliable, timely, systematic, and appropriately analyzed information (Shehzad et al., 2024). High quality green decisions enable organizations to evaluate environmental alternatives, identify potential environmental consequences, compare competing options, and select actions that are consistent with both organizational and environmental objectives (Yousaf, 2021). Further researchers highlighted that green decision making quality could improve the GCA. Liou et al. (2019) study also developed a data-driven hybrid decision-making model for green supplier evaluation and performance improvement, demonstrating the value of analytical information in environmental decision processes to remain companies competitive. Liou et al. (2021) study also applied the data-mining and multi-criteria decision-making techniques to green supplier evaluation and selection. These studies indicate that the quality of environmental decisions can be improved when organizations systematically collect, analyze, and compare relevant information. Thus, based on these factors, it is highlighting that companies which are more capable of making high-quality green decisions may be better positioned to develop GCA.

Green decision-making quality is being depended on the effective companies' ability on using the data-driven decision-making (DDDM). It is consisted of systematic use of data, analytical information, and empirical evidence to guide organizational decisions (Provost & Fawcett, 2013). Rather than relying exclusively on managerial intuition or subjective judgment, data-driven organizations use available information to identify patterns, evaluate alternatives, monitor outcomes, and support decision processes (Liou et al., 2019). DDDM importance is being increase due to rapid growth of digital technologies and organizational data. Brynjolfsson and McElheran (2016) studies documented the rapid adoption of data-driven decision-making practices among manufacturing firms. Awan et al. (2021) study further also demonstrated that big data analytics capability can support data-driven insights and decision-making associated with circular-economy performance. Xu and Lu (2026) recent study also examined data-driven decision-making in relation to sustainable value creation and reported that DDDM can contribute to sustainability-related outcomes, including pollution prevention and green innovation. These findings provide a basis for expecting that stronger DDDM capabilities can contribute to higher-quality green decision-making that could lead to improve the GCA.

DDDM effectiveness is not only depend only organizational available data but is also focused on the human capabilities which are required to understand and interpret quantitative information (Liou et al., 2019). This is being highlighting the significance of biostatistics knowledge and training. Biostatistics provides individuals with knowledge of statistical concepts and analytical procedures that can be used to collect, analyze, interpret, and communicate quantitative evidence (Salkind, 2017). As the biostatistics is being associated along with of medical and health research along with of fundamental principles like as statistical reasoning, evidence evaluation, uncertainty assessment, data interpretation, and quantitative analysis are relevant to broader evidence-based decision-making. Windish et al. (2007) found that medical residents demonstrated difficulties in understanding biostatistical concepts and research results, highlighting the importance of statistical competence for interpreting evidence. Al-Zahrani and Al-Khail (2015) similarly emphasized the importance of knowledge and attitudes toward biostatistics and research methods. To remove this barrier, training could be strengthen such kind of capabilities thorough providing the individuals along with the opportunities to learn and apply statistical methods. For instance, Barreto et al. (2020) reported improvements in research and biostatistics knowledge and confidence following a structured training program. da Silva and Moura (2020) also found that the use of statistical software and technology in medical education could contribute to changes in attitudes toward statistics and support statistical learning. These prior studies highlighting that companies with the stronger knowledge and training may be better able to understand organizational data, evaluate analytical results, recognize patterns, and use quantitative evidence when making decisions (Salkind, 2017). Therefore, biostatistics knowledge and training may provide an important human foundation for effective DDDM to improve the companies GCA.

In addition to prior knowledge and training, the biostatistics attitude could also influence the extent to which statistical information is accepted and used in decision-making. Biostatistics attitude refers to an individual's perceptions, beliefs, confidence, interest, and disposition toward statistics and statistical activities (Liou et al., 2019). A person may possess statistical knowledge but may not necessarily use it if they perceive statistics as difficult, irrelevant, or threatening. Schau et al. (1995) demonstrated that attitudes toward statistics involve several dimensions, including affect, cognitive competence, value, and difficulty. These dimensions indicate that individuals' perceptions of statistics can influence their engagement with statistical learning and application. In other perspective, Milic et al. (2016) study also emphasized the significance of attitude toward statistics and cognitive competence in applied statistical education. Dadaş and Suner (2026) further empirical study also reported the relationship between attitudes toward statistics and biostatistics achievement among medical students. Li et al. (2024) similarly examined attitudes toward biostatistics education and highlighted the importance of students' perceptions and attitudes in statistical education. In addition to these, other study also highlighted that individuals who have more positive attitudes toward quantitative analysis, then they may be more willing to engage

with data, interpret statistical findings, and incorporate analytical evidence into their decisions. Thus, biostatistics attitude may contribute to DDDM through encouraging the active use of statistical information rather than simply possessing statistical knowledge which could lead to improve the GCA.

Another important antecedent of data-driven decision-making (DDDM) is biostatistics research. It consisted of systematic application of statistical methods to generate, analyze, interpret, and communicate quantitative evidence. [Provost and Fawcett \(2013\)](#) emphasized that data science and data-driven decision-making are closely connected because analytical methods transform raw data into meaningful information that supports organizational decisions. On the other hand, [Windish et al. \(2007\)](#), [Al-Zahrani and Al-Khail \(2015\)](#), and [Barreto et al. \(2020\)](#) studies also examined that statistical knowledge, research competence, and statistical training in healthcare-related contexts. This concentration creates a research gap concerning whether biostatistical research capability can contribute to organizational DDDM that could lead to enhance GCA through better-informed sustainability practices. Furthermore, digital technology is an also important factor to improve DDDM that could increase the GCA. Digital technology provided the infrastructure through which organizational data can be collected, stored, processed, integrated, analyzed, and communicated ([Vial, 2019](#)). [Verhoef et al. \(2021\)](#) similarly emphasized that digital transformation involves integrating digital technologies into organizational processes and strategies. [Wamba et al. \(2017\)](#) demonstrated that big data analytics can contribute to firm performance through organizational capabilities, while [Mikalef et al. \(2020\)](#) found that big data analytics capabilities can influence competitive performance through dynamic and operational capabilities. These prior studies highlighted that digital technology significantly strengthen the organizational ability to transform environmental and operational data into actionable information, which can improve green decision-making quality and ultimately increase GCA through supporting efficient resource use, environmental innovation, and sustainability oriented competitive strategies.

With the significance of above factors to improve the GCA, still has various gaps in the prior literature. Prior literature DDDM has predominantly focused on big data analytics, business intelligence, information technology, and digital capabilities as important organizational resources for generating insights and supporting decision-making ([Gupta & George, 2016](#); [Wamba et al., 2017](#)) and focused on firm performance. [Gupta and George \(2016\)](#) and [Wamba et al. \(2017\)](#) emphasized the role of analytics capabilities in creating organizational value and improving performance. These prior studies have limited attention on biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology as complementary antecedents of organizational DDDM to improve GCA. Existing studies have generally examined technological and analytical capabilities separately rather than explaining how statistical research capability, statistical orientation, statistical knowledge and training, and digital infrastructure can jointly strengthen DDDM which could lead to improve the GCA. Further important gap is that there is little attention has been focused on impact of DDDM on GCA. Previous sustainability-oriented studies have examined data analytics in relation to circular economy, green supplier selection, sustainability, and environmental performance ([Awan et al., 2021](#)), while green competitive advantage studies have primarily emphasized green innovation, green capabilities, green strategies, and environmental orientation ([Ge et al., 2018](#); [Zameer et al., 2022](#)). While limited attention has been focused on how the DDDM contributes to GCA through the quality of green decisions. Therefore, this study is being different from prior studies in a critical way by developing an integrated sequential framework in which biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology serve as antecedents of DDDM; DDDM functions as a mediating organizational capability; green decision-making quality functions as an intermediate outcome and further explanatory mechanism; and green competitive advantage represents the ultimate dependent variable. This differentiation is especially important because the analytics capabilities have been shown to create organizational value through improved capabilities and processes ([Gupta & George, 2016](#); [Wamba et al., 2017](#)), while green innovation and green capabilities have been associated with competitive advantage ([Ge et al., 2018](#); [Zameer et al., 2022](#)). After filling the previous gaps, study focused on improving the pharmaceutical manufacturing companies GCA through improving DDDM process after focusing on various analytical techniques and digital technologies.

The study with the specific objective contributed that pharmaceutical organizations could strengthen their GCA through developing employees' biostatistical knowledge and training, fostering positive attitudes toward statistical evidence, strengthening biostatistical research capabilities, and investing in digital technologies that support data-driven and environmentally responsible decision-making. From a practical perspective, the framework suggests that organizations seeking to strengthen green competitive advantage may need to develop not only green technologies and environmental strategies but also the human analytical capabilities and digital infrastructure required to make evidence-based environmental decisions. Study was further divided into four chapter which were related to literature review which covered both of theoretical and empirical part. Research methods which covered research design and sampling technique. The data analysis to test study hypothesis. Lastly, discussion and implications of study results.

2. Literature Review

2.1 Biostatistics Research and Data-Driven Decision-Making

Biostatistics research can be defined as the systematic application of statistical principles and methods to the collection, organization, analysis, interpretation, and presentation of data in biological, medical, health, and related research contexts (Al-Zahrani & Al-Khail, 2015). It provides researchers with the methodological tools required to transform raw observations into reliable and interpretable evidence (Windish et al., 2007). Biostatistical methods help researchers identify relationships, estimate effects, evaluate uncertainty, test hypotheses, and distinguish meaningful findings from random variation (Altman, 1991). Consequently, biostatistics research provides an important foundation for evidence-based decision-making because decisions based on systematically analyzed evidence are less dependent on unsupported assumptions or personal intuition (Guyatt et al., 1995). Data-driven decision-making (DDDM), meanwhile, refers to the systematic use of data, quantitative evidence, and analytical information to identify problems, evaluate alternatives, and select appropriate decisions (Provost & Fawcett, 2013). The quality of DDDM therefore depends partly on the quality of the analytical evidence available to decision-makers (Davenport & Harris, 2007). When individuals and organizations engage more extensively with biostatistical research, they can develop greater exposure to systematic data analysis and evidence interpretation (Al-Zahrani & Al-Khail, 2015). Such exposure can help decision-makers understand statistical relationships and uncertainty and consequently use empirical evidence more effectively when making decisions (Windish et al., 2007). At the organizational level, analytical approaches are increasingly recognized as an important basis for converting data into actionable knowledge (Chen & Chang, 2013). Thus, biostatistics research can provide an important evidence-generating foundation for DDDM by improving the availability and interpretation of reliable quantitative information.

Empirical studies provide support for the argument that biostatistical research and statistical exposure contribute to evidence interpretation. Windish et al. (2007) found that medical residents with previous biostatistics training demonstrated greater statistical knowledge, indicating that exposure to statistical research methods improves the ability to understand quantitative evidence. Al-Zahrani and Al-Khail (2015) similarly found that previous exposure to evidence-based medicine and biostatistics was associated with participants' knowledge and attitudes toward statistical concepts. In Pakistan, Butt and Khan (2008) reported that postgraduate medical trainees and supervisors recognized the importance of biostatistics and epidemiology while also identifying weaknesses in existing statistical education. Biostatistical competence has consequently been recognized as an important element of evidence interpretation and professional decision-making (Al-Zahrani & Al-Khail, 2015; Windish et al., 2007). At the organizational level, Brynjolfsson and McElheran (2016) further showed that DDDM adoption among U.S. manufacturing plants increased substantially and was associated with complementary resources such as information technology and educated workers. Although these studies do not all directly test the specific relationship *between* biostatistics research *and* DDDM, they provide empirical support for the underlying mechanism where argued biostatistical research strengthens the production and interpretation of quantitative evidence, while DDDM requires organizations and decision-makers to use such evidence systematically. Therefore, greater engagement with biostatistics research is expected to enhance data-driven decision-making and accordingly hypothesis is,

H1: Biostatistics research has a positive and significant effect on data-driven decision-making.

2.2 Biostatistics Attitude and Data-Driven Decision-Making

Biostatistics attitude refers to an individual's perceptions, beliefs, confidence, interest, willingness, and feelings toward statistics and the use of statistical methods (Schau et al., 1995). A positive attitude indicates that individuals perceive statistical knowledge as useful, relevant, understandable, and valuable, whereas a negative attitude may involve statistical anxiety, low confidence, or perceptions that statistics is difficult (Chew & Dillon, 2014). Attitude is particularly important because the availability of statistical information does not automatically ensure that individuals will use it when making decisions (Gal et al., 1997). Decision-makers must be willing to engage with data, interpret analytical results, and consider quantitative evidence before incorporating it into their decisions (Provost & Fawcett, 2013). A favorable attitude toward biostatistics can therefore encourage individuals to engage more actively with statistical information and develop greater confidence in using quantitative evidence (Salkind, 2017). In contrast, negative perceptions of statistics may discourage individuals from examining analytical results and may increase reliance on experience or intuition (Chew & Dillon, 2014). This is particularly relevant to DDDM because DDDM requires not only technological access to data but also human willingness to use analytical information in decision processes (Davenport & Harris, 2007). Research on statistics education further suggests that attitudes toward statistics are connected with students' engagement and achievement (Onwuegbuzie & Wilson, 2003; Schau et al., 1995). Thus, a positive biostatistics attitude can provide an important psychological foundation for accepting, interpreting, and using quantitative evidence in decision-making.

Empirical studies provide substantial evidence concerning the importance of attitudes toward biostatistics. For instance, Al-Zahrani and Al-Khail (2015) found that medical residents' attitudes toward biostatistics were related to their exposure to research and statistical training. A multi-site study by Milic et al. (2016) found that students' cognitive

competence attitudes toward statistics were positively related to achievement in statistics, with the meta-analysis reporting a significant positive association between cognitive competence and statistical achievement. [Santabábara and López-Antón \(2020\)](#) found that medical students generally viewed statistics as useful and that attitudes toward statistics were related to performance in biostatistics. Their meta-analytic study also concluded that positive attitudes toward statistics were associated with higher achievement in biostatistics ([Dadaş & Suner, 2026](#)). More recently, [Li et al. \(2024\)](#) developed and evaluated the Chinese version of the Survey of attitudes toward statistics and found that attitudes toward biostatistics could be reliably measured and that students continued to perceive biostatistics as both important and challenging. [Cantas Turkis and Varol \(2026\)](#) further identified distinct attitude profiles among medical students and residents and emphasized that biostatistics is important for evidence interpretation and clinical decision-making. These findings indicate that attitudes influence how individuals engage with statistical information. Since DDDM requires individuals to accept and actively use quantitative evidence, a favorable attitude toward biostatistics is expected to facilitate DDDM and accordingly hypothesis is.

H2: Biostatistics attitude has a positive and significant effect on data-driven decision-making.

2.3 Biostatistics Knowledge and Training and Data-Driven Decision-Making

Biostatistics knowledge and training refer to an individual's understanding of statistical concepts and the educational experiences through which statistical competencies are developed ([Windish et al., 2007](#)). Biostatistical knowledge includes concepts such as data interpretation, probability, hypothesis testing, statistical inference, research design, relationships among variables, and assessment of uncertainty ([Altman, 1991](#)). Training provides individuals with opportunities to apply these concepts to practical research and decision-making problems ([Salkind, 2017](#)). These capabilities are particularly important for DDDM because the availability of large amounts of data does not necessarily result in effective decisions if decision-makers cannot understand the meaning, reliability, and limitations of the information ([Provost & Fawcett, 2013](#)). Data-driven organizations require individuals who can evaluate analytical outputs, identify meaningful patterns, interpret statistical findings, and communicate evidence to decision-makers ([Chen & Chang, 2013](#)). Analytical capability is therefore partly dependent on human knowledge and skills that allow data resources to be transformed into organizational value ([Gupta & George, 2016](#)). [Mikalef et al. \(2020\)](#) similarly conceptualized big data analytics capability as involving resources and competencies that enable organizations to transform data into useful outcomes. Therefore, biostatistics knowledge and training can enhance DDDM by developing the human capacity required to understand quantitative information and apply statistical evidence to decision processes. Individuals who possess stronger statistical knowledge are more likely to understand the strengths and limitations of data and consequently use evidence more systematically in decision-making.

Empirical studies support the importance of statistical training and knowledge. [Windish et al. \(2007\)](#) found that residents with previous biostatistics training demonstrated higher levels of statistical knowledge than residents without such training. [Al-Zahrani and Al-Khail \(2015\)](#) similarly reported that previous training in evidence-based medicine and related statistical subjects was associated with greater knowledge of biostatistics. [Butt and Khan \(2008\)](#) identified weaknesses in postgraduate biostatistical education in Pakistan and emphasized the need to strengthen training in biostatistics and epidemiology. In another educational study, [da Silva and Moura \(2020\)](#) examined the use of RStudio in introductory biostatistics education and found significant improvements in several dimensions of students' attitudes toward statistics following the course. [Milic et al. \(2016\)](#) also demonstrated that students' perceptions of cognitive competence in statistics were positively related to statistical achievement. At the organizational level, [Gupta and George \(2016\)](#) argued that big data analytics capability requires tangible, human, and intangible resources, while [Mikalef et al. \(2020\)](#) showed that analytics capabilities can contribute to competitive performance through organizational capabilities. These findings suggest that analytical knowledge and training are necessary for converting data into useful evidence. Although much of the biostatistics literature has focused on medical education rather than organizational DDDM, the underlying mechanism is relevant: statistical knowledge and training increase the ability to interpret quantitative evidence, and DDDM depends on precisely this capability. Accordingly, stronger biostatistics knowledge and training are expected to improve data-driven decision-making and accordingly hypothesis is.

H3: Biostatistics knowledge and training have a positive and significant effect on data-driven decision-making.

2.4 Digital Technology and Data-Driven Decision-Making

Digital technology refers to technological systems and applications that enable organizations to collect, store, process, integrate, analyze, communicate, and utilize digital information ([Vial, 2019](#)). It includes information systems, databases, cloud computing, artificial intelligence, big data analytics, Internet of Things technologies, and digital platforms ([Bharadwaj et al., 2013](#)). Digital technologies have become increasingly important because organizations now generate large volumes of data through customers, employees, suppliers, transactions, production processes, and digital interactions ([Verhoef et al., 2021](#)). Appropriate digital infrastructure enables organizations to integrate information from multiple sources and make that information available to decision-makers in a timely manner ([Verhoef et al., 2021](#)). Digital technology therefore provides

an important infrastructure for DDDM because analytical decisions require systems capable of collecting, storing, processing, and presenting relevant information (Chen & Chang, 2013). Digital transformation can also increase organizational connectivity and information availability, thereby changing how decisions are made (Vial, 2019). Nambisan et al. (2017) emphasized that digital technologies transform organizational innovation and information processes, while Verhoef et al. (2021) identified digital capabilities as an important component of organizational transformation. Consequently, digital technology can facilitate DDDM by reducing information barriers, improving data accessibility, supporting advanced analytics, and enabling real-time or near-real-time decision support.

Furthermore, Brynjolfsson and McElheran (2016) empirical study found that the adoption of DDDM among U.S. manufacturing plants increased considerably and that adoption was associated with information technology and educated workers. Wamba et al. (2017) found that big data analytics capabilities can create business value through organizational capabilities, demonstrating the importance of technological and analytical resources for converting data into organizational outcomes. Mikalef et al. (2020) similarly found that big data analytics capabilities influence competitive performance through dynamic and operational capabilities. Recent research by Goraya et al. (2026) further demonstrates that digital transformation strategy and business analytics capability support DDDM and organizational performance. Parvez et al. (2026) reported that Green IoT contributes to DDDM in sustainability-oriented organizational settings. Recent empirical research also shows that big data technologies can strengthen data-driven decision processes and resource optimization for corporate green development. These findings demonstrate that digital technologies do more than store information; they create the infrastructure through which data can be transformed into analytical evidence. Therefore, stronger digital technology capabilities are expected to facilitate data-driven decision-making and accordingly hypothesis is.

H4: Digital technology has a positive and significant effect on data-driven decision-making.

2.5 Data-Driven Decision-Making and Green Decision-Making Quality

Data-driven decision-making refers to the systematic use of empirical data, quantitative information, analytics, and evidence to identify problems, evaluate alternatives, make decisions, and monitor outcomes (Provost & Fawcett, 2013). Green decision-making quality refers to the extent to which decisions concerning environmental sustainability are accurate, timely, evidence-based, comprehensive, and appropriate after considering relevant environmental and organizational criteria. Data-driven approaches can allow decision-makers to evaluate these criteria systematically rather than relying primarily on subjective judgment (Liou et al., 2019). Data analytics can also identify patterns in environmental performance, evaluate alternative suppliers, predict resource requirements, and assess potential environmental consequences (Liou et al., 2021). When organizations use reliable and relevant data, decision-makers can compare environmental alternatives more objectively and make decisions that are better aligned with sustainability objectives (Wamba et al., 2017). Thus, DDDM can improve green decision-making quality by strengthening the evidence base, reducing uncertainty, supporting multiple-criteria evaluation, and enabling more systematic environmental assessment.

Liou et al. (2019) empirical research highlighted developed a data-driven hybrid multiple-attribute decision-making model for green supplier evaluation and demonstrated how data mining and decision-analysis techniques can support environmental supplier assessment. Liou et al. (2021) study also similarly combined data mining techniques with multiple-criteria decision-making to improve green supplier evaluation and selection. Huang et al. (2023) examined the relationship between lean practices, DDDM, and environmental performance and emphasized the role of data-driven approaches in sustainable manufacturing. Anwar et al. (2024) examined big data analytics adoption in the recycling sector and investigated its implications for decision quality and environmental performance. Xu and Lu (2026) provide particularly recent evidence, finding that DDDM contributes to sustainable value creation through pollution prevention, green innovation, sustainability information disclosure, and sustainability-oriented value creation. Recent evidence therefore indicates that DDDM can improve the use of information for environmental management and sustainability outcomes. Although previous studies have often measured environmental performance or sustainability value rather than the exact construct of *green decision-making quality*, their findings provide a logical empirical foundation for expecting DDDM to improve the quality of green decisions. Therefore, the following hypothesis is,

H5: Data driven decision-making has a positive and significant effect on green decision-making quality.

2.6 Green Decision Making Quality and Green Competitive Advantage

Green decision-making quality refers to the extent to which organizational decisions concerning environmental sustainability are based on accurate information, appropriate analysis, relevant environmental criteria, and systematic evaluation of alternatives. Green competitive advantage refers to competitive benefits that organizations obtain through environmentally oriented resources, capabilities, products, processes, technologies, and strategies (Song & Yu, 2018). The relationship between green decision-making quality and green competitive advantage can be explained through the natural-resource-based view, which argues that environmental capabilities can become important sources of competitive advantage when they create value and are difficult for competitors to imitate (Hart, 1995). Green decision-making quality may therefore represent an important organizational capability through which sustainability information is converted into strategic action.

When firms make better environmental decisions, they may be more capable of developing green products, adopting green technologies, improving resource efficiency, and responding to environmental pressures (Song & Yu, 2018). These capabilities can subsequently contribute to green competitive advantage through differentiation, innovation, efficiency, and improved market positioning (Ge et al., 2018). Thus, the quality of green decisions can be viewed as an upstream capability that supports the development and implementation of environmentally oriented competitive strategies.

Ge et al. (2018) empirically examined green innovation strategy and sustainable competitive advantage and found that green innovation strategy can contribute to sustainable competitive outcomes. Research on green dynamic capabilities similarly suggests that environmentally oriented organizational capabilities can support green innovation and competitive outcomes (Yousaf, 2021). More recent research by Zameer et al. (2024) examined green competitive advantage in a big-data environment and emphasized the role of organizational learning and green marketing capabilities in strengthening green competitive advantage. Recent empirical evidence from Pakistani manufacturing firms also indicates significant relationships among green entrepreneurship, green innovation, and green competitive advantage (Shehzad et al., 2024). The broader sustainability literature further indicates that DDDM can create sustainable value through pollution prevention and green innovation, which can ultimately support organizational performance (Xu & Lu, 2026). Although these studies generally investigate green innovation, green capabilities, environmental performance, or green competitive advantage rather than the exact construct of green decision-making quality, they collectively establish the theoretical and empirical basis for linking the quality of environmental decisions with competitive outcomes. The present study therefore extends existing literature by proposing that organizations capable of making higher-quality green decisions are better positioned to develop and utilize green capabilities that contribute to green competitive advantage and accordingly hypothesis is,

H6: Green decision-making quality has a positive and significant effect on green competitive advantage.

3. Research Methods

The study aimed to test the influence of ERM on FP with mediating influence of SMC. RC also used to increase the effect of ERM on FP. For this purpose, researchers employed the quantitative research approach. The quantitative research approach provides objective, measurable, and statistically analyzable data, allowing researchers to test hypotheses and examine relationships between variables. It increases the reliability, generalizability, and statistical rigor by using standardized instruments and larger samples. Data was collected using self-administered questionnaire and for this cross sectional research design was employed. A cross sectional research design efficiently collects data at a single point in time, enabling researchers to examine relationships among variables quickly and cost-effectively.

3.1 Research Instrument and Framework

Study research instrument was adopted from prior studies where it was already tested and used. Biostatistics knowledge and training was comprised from 5 items, biostatistics research comprised from 3 items, and biostatistics research comprised from 14 items. These three constructs items were taken from the study of Javali and Sunkad (2016). Furthermore, technology capability was comprised from 5 items of Cheng et al. (2025). Data driven decision making also comprised from 5 items (Ashaari et al., 2021). Decision making quality comprised from 3 items (Visinescu et al., 2017). Lastly, green competitive advantage comprised from 11 items (Chen & Chang, 2013). Each of above items were ranked on five point Likert Scale. Above constructs are depicted in Figure.1 below,

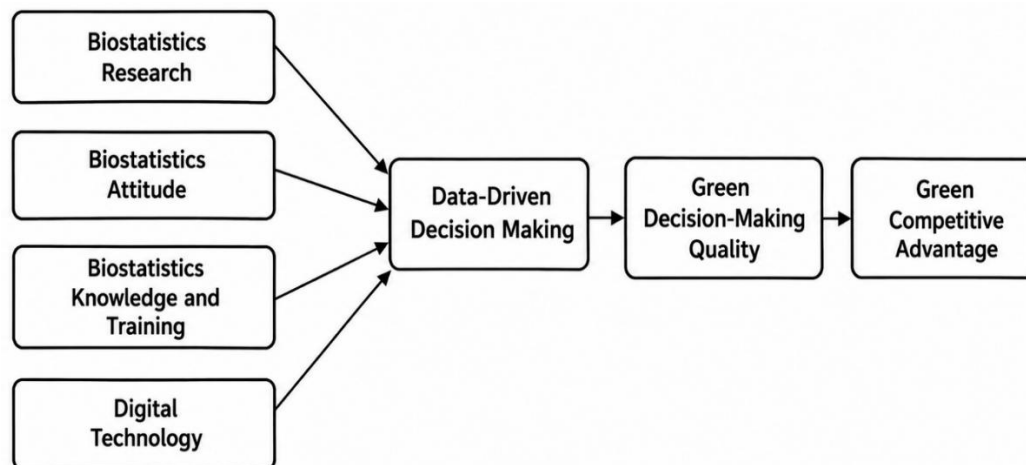


Figure 1: Research Framework

3.2 Population and Sampling Technique

The population of this study comprised employees working in the pharmaceutical sector. A total of 450 questionnaires were distributed among employees of pharmaceutical organizations, of which 300 usable and complete questionnaires were returned and considered valid for statistical analysis, representing a 66.7% usable response rate. The respondents were selected using a convenience sampling technique, a non-probability sampling method in which participants are selected based on their accessibility and willingness to participate. Under the domain of non-probability researchers used the convenient sampling technique which was being considered an appropriate for the current study complete sampling framework of pharmaceutical sector employees and randomly accessing employees across different organizations can be difficult. Furthermore, this technique is also enabling to the researchers to collect data effectively within the practical constraints of time, accessibility, and resources (Etikan et al., 2016). Therefore, this technique is considered to be more effective technique for the current study.

Table 1: Sampling Frame

Sampling Aspect	Description
Target Population	Employees working in the pharmaceutical sector
Questionnaires Distributed	450
Valid Responses	300
Usable Response Rate	66.7%
Sampling Technique	Convenience sampling
Nature Of Sampling	Non-probability sampling

4. Data Analysis and Results

4.1 Demographic Results

This section shown the demographic profile of respondents where most of respondents were male (60%), while females represented 40% of the sample. On the other hand, most respondents were aged 31–40 years (40%), followed by those aged 20–30 years (35%). Regarding education, half of the respondents held a Master's degree (50%), while 30% had a Bachelor's degree. In terms of experience and job position, most respondents had 5–10 years of experience (40%) and were middle-level managers (40%). Demographic results are in Table.2.

Table 2: Respondents Profile

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	180	60.0
	Female	120	40.0
Age	20–30 years	105	35.0
	31–40 years	120	40.0
	41–50 years	60	20.0
	Above 50 years	15	5.0
	More than 15 years	30	10.0
Education	Bachelor's degree	90	30.0
	Master's degree	150	50.0
	MPhil/MS	45	15.0
	PhD	15	5.0
Work Experience	Less than 5 years	105	35.0
	5–10 years	120	40.0
	11–15 years	45	15.0
	More than 15 years	30	10.0
Job Position	Junior/Operational Staff	90	30.0
	Middle-Level	120	40.0
	Management		
	Senior Management	60	20.0
	Other Professional Staff	30	10.0

4.2 Structural Equation Modeling

The researchers used the AMOS based Structural Equation Modeling (SEM) which was used to examine the structural relationships among the study variables and to assess the proposed mediation and moderation effects. It is particularly appropriate for simultaneously estimating multiple relationships while accounting for measurement error and assessing the overall model fit (Hair Jr et al., 2021). Using AMOS, analysis was conducted in two models, measurement and structural model.

4.2.1 Measurement Model

The measurement model assessed using two validity technique namely convergent validity and discriminant validity which are assessed in below sections.

4.2.1.1 Outer Loadings

First criteria to assess the model is to check the factor loadings which shown the strength of the relationship between each observed indicator and its underlying latent construct. Loading value of greater than 0.70 is considered to be more acceptable because it shown that the construct explains a effective proportion of indicator's variance (Hair Jr et al., 2021). Higher factor loadings provide stronger evidence that the indicators adequately represent their respective constructs (Hair Jr et al., 2021). Outer loadings values are in Table.3 and Figure.2 below,

Table 3: Outer Loadings

Construct	Item	Loading
Perceptions of Biostatistics & Research	PBR1	0.938
	PBR2	0.923
	PBR3	0.914
Attitude Towards Biostatistics	ATB1	0.894
	ATB2	0.908
	ATB3	0.898
	ATB4	0.901
	ATB5	0.894
	ATB6	0.905
	ATB7	0.887
	ATB8	0.884
	ATB9	0.880
	ATB10	0.893
	ATB11	0.883
Knowledge & Training	ATB12	0.908
	ATB13	0.893
	ATB14	0.904
	PKT1	0.915
	PKT2	0.924
Technology Capability	PKT3	0.926
	PKT4	0.920
	PKT5	0.903
	TC1	0.931
	TC2	0.913
Data-Driven Decision Making	TC3	0.920
	TC4	0.929
	TC5	0.913
	DDDM1	0.922
	DDDM2	0.911
Green Decision-Making Quality	DDDM3	0.924
	DDDM4	0.924
	DDDM5	0.914
Green Competitive Advantage	GDMQ1	0.918
	GDMQ2	0.932
	GDMQ3	0.934
Green Competitive Advantage	GCA1	0.902
	GCA2	0.902
	GCA3	0.904
	GCA4	0.889
	GCA5	0.903
	GCA6	0.890
	GCA7	0.895
	GCA8	0.910
	GCA9	0.909
	GCA10	0.897
	GCA11	0.915

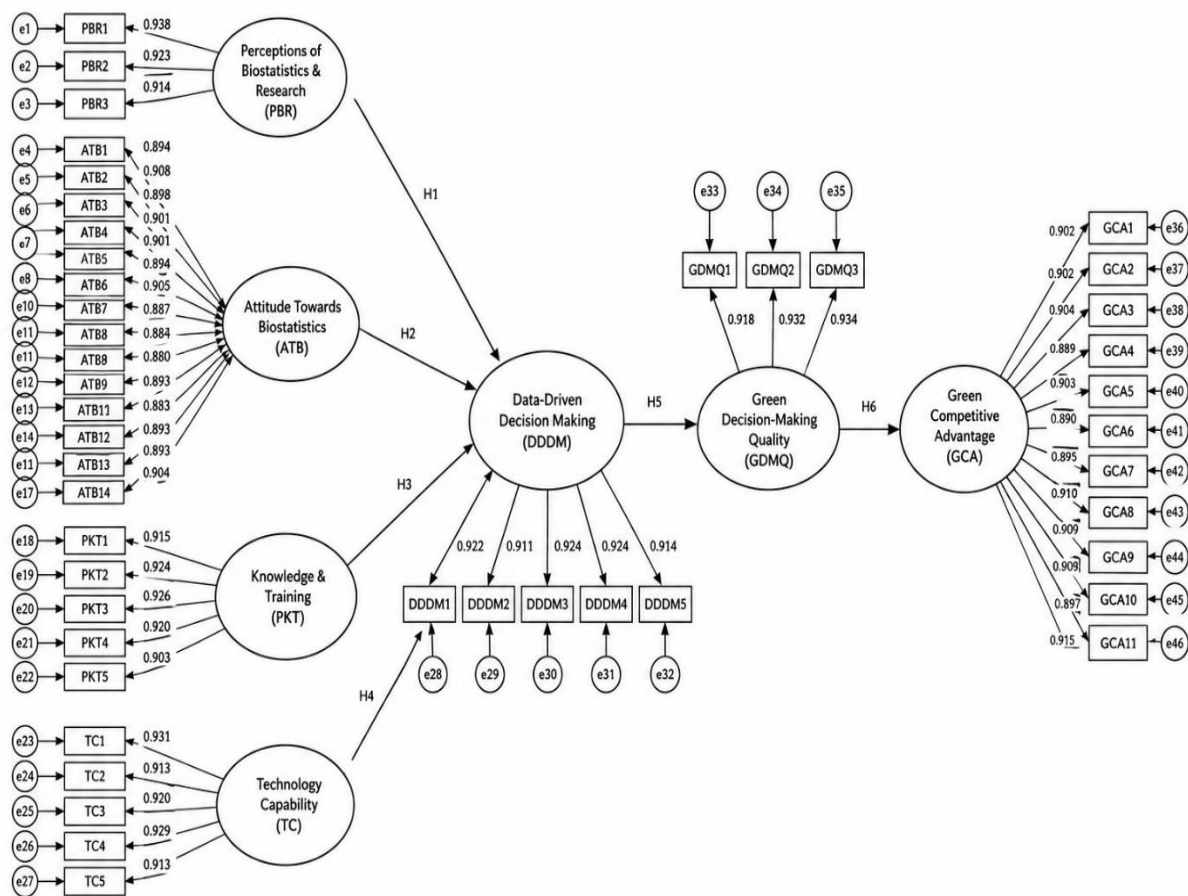


Figure 2: Measurement Model

4.2.1.2 Convergent Validity

In measurement model, we also have to assess the internal consistency reliability of the item which is being used to measure the study construct. For the internal consistency, alpha value is considered to be more effective and threshold value is greater than 0.70 is considered to be more effective, which is showing a satisfactory level of internal consistency among the measurement items (Hair Jr et al., 2021). On the other hand, convergent validity was being assessed to extent where indicators of the same constructs are being shared a high proportion of common variance. It is generally assessed using factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). An AVE value of 0.50 or above indicates that the construct explains at least half of the variance in its indicators, supporting convergent validity (Hair Jr et al., 2021). All of values in Table.3 and Table.4 fulfil the requirement of convergent validity that shown that construct is valid for further analysis.

Table 4: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
PBR	0.916	0.947	0.856
ATB	0.981	0.983	0.801
PKT	0.953	0.964	0.842
TC	0.955	0.965	0.848
DDDM	0.954	0.964	0.845
GDMQ	0.919	0.949	0.861
GCA	0.977	0.979	0.813

4.2.1.3 Discriminant Validity

Discriminant validity in the constructs shown that each construct diagonal value should be greater than from below value. Among the various discriminant validity criteria's researchers used the Fornell–Larcker criterion to assess the discriminant validity through comparing the square root of the AVE of each construct with its correlations with other

constructs (Fornell & Larcker, 1981). Below in Table.5 results shown that constructs fulfill the requirement of discriminant validity.

Table 5: Discriminant Validity

	PBR	ATB	PKT	TC	DDDM	GDMQ	GCA
PBR	0.925						
ATB	0.202	0.895					
PKT	0.215	0.274	0.918				
TC	0.091	0.252	0.261	0.921			
DDDM	0.321	0.392	0.489	0.444	0.919		
GDMQ	0.227	0.148	0.325	0.287	0.514	0.928	
GCA	0.191	0.191	0.240	0.317	0.378	0.593	0.902

4.2.2 R Square

In the SEM, coefficient of determination is being shown the proportion of variance in the endogenous variable which is being explained through its predictor variable in structural model (Hair Jr et al., 2021). The findings shown that PBR, ATB, PKT, and TC collectively explain 42.2% of the variance in DDDM. DDDM explains 26.4% of the variance in GDMQ, while GDMQ explains 35.1% of the variance in GCA. These results in Table.6 showing the predictive power of the model.

Table 6: Coefficient of Determination

Endogenous Construct	R ²	Variance Explained	Coefficient of Determination
DDDM	0.422	42.2%	Yes
GDMQ	0.264	26.4%	Yes
GCA	0.351	35.1%	Yes

4.2.3 Multicollinearity

In the SEM model, multicollinearity is being to be occurred when the two or more predictors are being more correlated which making it difficult for determining their segregated effects on the dependent variable and potentially distorting the estimated coefficients and its recommended values is less than 5 (Hair Jr et al., 2021). Below, Table.7 shown that each values is less than 5 which are being ranged between 1.0 to 1.16, which is showing, there is no issue of multicollinearity in study constructs.

Table 7: Variance Inflation Factor

Endogenous Construct	Relationship	VIF
DDDM	PBR → DDDM	1.073
DDDM	ATB → DDDM	1.149
DDDM	PKT → DDDM	1.160
DDDM	TC → DDDM	1.115
GDMQ	DDDM → GDMQ	1.000
GCA	GDMQ → GCA	1.000

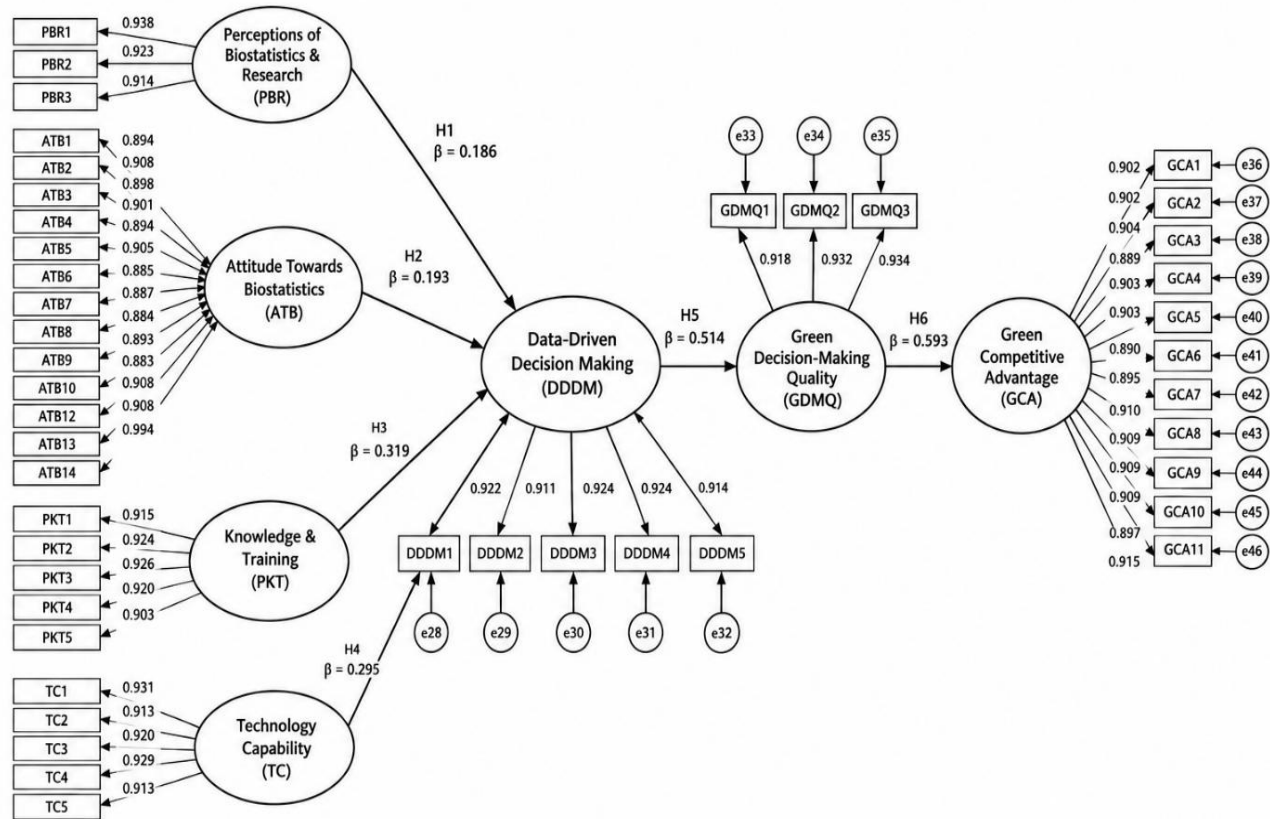
4.2.4 Path Coefficients and Hypothesis Testing

This section represents hypothesis results. SEM model results shown that biostatistics research has positive and significant effect on the data driven decision making ($\beta = 0.186$, $SE = 0.048$, $t = 3.853$, $p < 0.001$). Therefore, H1 is supported. The positive coefficient suggests that higher perceptions of biostatistics research are associated with greater use of DDDM practices. ATB has a positive and statistically significant effect on DDDM ($\beta = 0.193$, $SE = 0.050$, $t = 3.880$, $p < 0.001$). Hence, H2 is supported. This finding indicates that a more favorable attitude toward biostatistics is associated with stronger DDDM. PKP also demonstrated a positive and significant effect on DDDM ($\beta = 0.319$, $SE = 0.049$, $t = 6.462$, $p < 0.001$). Thus, H3 is supported.

Among the four antecedents of DDDM, this path has the largest coefficient, indicating a comparatively stronger association in this simulated dataset. TC has a positive and significant effect on DDDM ($\beta = 0.295$, $SE = 0.048$, $t = 6.160$, $p < 0.001$). Therefore, H4 is supported. The result indicates that greater technological capability is associated with increased data-driven decision-making. DDDM also has a positive and significant effect on GDMQ ($\beta = 0.514$, $SE = 0.049$, $t = 10.588$, $p < 0.001$). Consequently, H5 is supported. GDMQ also has a positive and significant effect on GCA ($\beta = 0.593$, $SE = 0.045$, $t = 13.112$, $p < 0.001$). Therefore, H6 is supported. Path coefficients results are in Table.8.

Table 8: Hypothesis Results

Relationship	β	SE	t-value	Decision
PBR $\rightarrow$ DDDM	0.186	0.048	3.853	Supported
ATB $\rightarrow$ DDDM	0.193	0.050	3.880	Supported
PKT $\rightarrow$ DDDM	0.319	0.049	6.462	Supported
TC $\rightarrow$ DDDM	0.295	0.048	6.160	Supported
DDDM $\rightarrow$ GDMQ	0.514	0.049	10.588	Supported
GDMQ $\rightarrow$ GCA	0.593	0.045	13.112	Supported

**Figure 3:** Structural Model Results

5. Discussion

Results shown that biostatistics research has a positive and significant effect on DDDM. This result suggests that pharmaceutical manufacturing companies that place greater emphasis on research-based statistical analysis are more likely to use quantitative evidence when making organizational and operational decisions. In manufacturing environments, statistical research can help managers identify production variations, evaluate quality problems, analyze process performance, and make evidence-based operational choices. Result is consistent with [Chavez et al. \(2022\)](#), who emphasized that the effective use of data can support sustainability-oriented decision-making within manufacturing organizations. Their study showed that manufacturing firms increasingly recognize data utilization as an important mechanism for developing sustainable and resilient operations. [Huang et al. \(2023\)](#) study also identified that DDDM as an important component of sustainable manufacturing practices, particularly where statistical and analytical information is used to improve organizational processes. Therefore, the significant relationship suggests that research oriented statistical capabilities can contribute to the development of DDDM in pharmaceutical manufacturing companies that could enhance the company's GCA.

Biostatistics Attitude has also a positive and significant effect on DDDM. The finding indicates that when employees and managers in pharmaceutical manufacturing companies have a favorable attitude toward statistical analysis, they are more likely to recognize the value of quantitative evidence and incorporate statistical information into organizational decisions. This is important because the effectiveness of analytical technologies does not depend only on their availability; employees must also be willing to use analytical information when making decisions. [Chavez et al. \(2022\)](#) observed that

although manufacturing organizations recognize the potential of data-driven approaches for sustainability, the transition toward fully data-driven operations remains incomplete. This indicates that organizational acceptance and willingness to utilize data are important elements of successful data-driven transformation. Similarly, [Huang et al. \(2023\)](#) emphasized the importance of employee motivation and organizational culture alongside data-driven decision-making in supporting sustainable manufacturing practices. Thus, the significant finding can be interpreted as indicating that positive attitudes toward statistical analysis may encourage manufacturing personnel to utilize data more actively in operational DDDM which could increase the companies GCA.

Biostatistics Knowledge and Training has a positive and significant effect on Data-Driven Decision Making. Among the four antecedents of DDDM, this relationship has a comparatively stronger coefficient and effect size, suggesting that knowledge and training in statistical analysis can play an important role in developing data-driven decision-making capabilities. In pharmaceutical manufacturing companies, employees with appropriate statistical knowledge can interpret production information, analyze quality indicators, identify process deviations, evaluate operational alternatives, and transform raw data into meaningful managerial information. [Chavez et al. \(2022\)](#) emphasized that effective data utilization requires organizational capabilities that allow firms to transform available data into useful information for sustainability and operational decision-making. Furthermore, [Huang et al. \(2023\)](#) identified data-driven decision-making and employee-related factors as important elements of sustainable manufacturing practices. Their study particularly linked data-driven approaches with improvements in environmental performance within manufacturing contexts. Accordingly, result suggested that pharmaceutical manufacturing companies can strengthen their DDDM capability by investing in employees' statistical knowledge, analytical skills, and relevant training programs which might helped to be a leading sector in the global market.

Digital technology has a positive and significant effect on DDDM. The result indicates that manufacturing organizations with stronger digital technology capabilities are better positioned to collect, process, integrate, and utilize information in organizational decision-making. Digital technologies can facilitate the availability of timely production, quality, supply-chain, energy, and environmental information, thereby allowing managers to make decisions based on current organizational data. [Chavez et al. \(2022\)](#) specifically argued that digital transformation creates opportunities for manufacturing firms to use data to enhance sustainability and develop more resilient and circular operations. Similarly, [Huang et al. \(2023\)](#) demonstrated the relevance of digital and analytical approaches to DDDM and sustainable manufacturing, emphasizing that DDDM can contribute to improved environmental performance. Therefore, the significant finding indicates that digital technological capability can provide the infrastructure necessary for pharmaceutical manufacturing companies to move toward systematic and evidence-based decision-making. Study further indicates that digital technology makes a meaningful contributed to improve the DDDM which might helped to increase the GCA.

On the other hand, DDM has a positive and significant effect on GDMQ. The relatively findings indicate that DDDM is an important factor associated with the GDMQ in pharmaceutical manufacturing companies. Manufacturing organizations generate substantial information concerning energy consumption, raw-material utilization, waste, emissions, production efficiency, logistics, and resource utilization. When such information is systematically collected and analyzed, managers can identify environmental problems and evaluate alternative production and operational strategies using objective evidence. [Chavez et al. \(2022\)](#) highlighted the potential of DDDM to support sustainable and resilient manufacturing operations, particularly through improved utilization of organizational and operational data. [Huang et al. \(2023\)](#) also linked DDDM with sustainable manufacturing practices and environmental performance, arguing that DDDM can support organizations in improving their environmental outcomes. Hence, finding indicates that pharmaceutical manufacturing companies can improve the GDMQ when environmental and operational decisions are supported by systematically collected and analyzed data which might improve the GCA of companies.

Lastly, GDMQ also has a positive and significant effect on GCA. The result suggests that pharmaceutical manufacturing companies that make higher-quality green decisions may be better positioned to develop competitive advantages associated with environmental and sustainability performance. Effective green decisions can influence resource efficiency, waste reduction, environmental compliance, production processes, product development, and the firm's ability to respond to growing environmental expectations. [Ahmadi-Gh and Bello-Pintado \(2022\)](#) found the same results where they examined that manufacturing sustainability outcomes make an important contribution to the competitive advantage of pharmaceutical manufacturing companies. Their findings demonstrate that effectively implemented sustainability practices can improve sustainability outcomes and subsequently contribute to competitive advantage. [Huang et al. \(2023\)](#) connected data-driven and sustainable manufacturing practices with environmental performance in the manufacturing industry. Therefore, finding indicates that GDMQ can represent an important organizational mechanism through which manufacturing firms translate sustainability-oriented decisions into competitive advantage. This increasing competitive advantage of pharmaceutical companies could helped to be leading partner in global market.

6. Implications

Various implication of study. From the theoretically, firstly, the study contributes to the existing literature by introducing and empirically testing an integrated framework of biostatistics research, biostatistics attitude, biostatistics knowledge and training, digital technology, DDDM, GDMQ, and GCA in the pharmaceutical manufacturing sector. As these relationships have been tested in the pharmaceutical context for the first time in this study, the findings provide a sector-specific contribution to the literature. Secondly, the study contributes through demonstrating that both human capabilities and technological resources are important for developing DDDM. The significant effects of biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology indicate that DDDM is not only dependent on technology but also on employees' statistical knowledge, training, and willingness to use quantitative evidence. Thirdly, the study extends sustainability and decision-making literature through establishing a sequential relationship between DDDM, GDMQ, and GCA. The significant relationship between DDDM and GDMQ, followed by the strong relationship between GDMQ and GCA, which shown that data-driven capabilities could provide an important mechanism for translating information into GDMQ and sustainability related GCA which could improve global acceptance of pharmaceutical sector.

Practically, firstly, pharmaceutical manufacturing companies should invest in statistical training and employee development because Biostatistics Knowledge and Training showed a meaningful relationship with DDDM. Employees should be trained to analyze production, quality, environmental, and operational data effectively. Secondly, managers should develop a positive organizational attitude toward statistical and evidence-based decision-making. Employees should be encouraged to use quantitative information rather than relying solely on experience or intuition when making operational and strategic decisions. Thirdly, manufacturing firms should strengthen their digital infrastructure and analytical technologies to facilitate timely collection, processing, and utilization of organizational data. Technology investments should be supported by appropriate employee training to ensure effective use. Fourthly, managers should integrate data analytics into green decision-making processes, particularly for monitoring energy consumption, waste, emissions, resource utilization, and production efficiency. Since DDDM has a strong relationship with green decision-making quality, systematic use of data can support more informed environmental decisions. Finally, pharmaceutical manufacturing companies should focus on improving the quality of green decisions because GDMQ demonstrated the strongest relationship with GCA. Thus, the study suggests that manufacturing firms can connect statistical capabilities and digital technologies with sustainability outcomes through developing a DDDM culture and improving the GDMQ.

7. Limitation and Future Directions

The study has various limitation which needs to be addressed in further study. Firstly, study was focused on the pharmaceutical sector which limited the generalizability for other sectors like as banking, healthcare, education, retail, and services. To address this limitation, further research could be conducted on different other sectors to increase research scope. Secondly, study focused on the cross-sectional research design where data collected on point in time that could not explain the data-driven decision-making and green competitive advantage develop over time. Therefore, to address this limitation further research could be explored on longitudinal research design. Lastly, future studies can extend the proposed framework by examining additional outcomes such as green innovation, environmental performance, operational efficiency, and organizational sustainability, while mixed-method and qualitative approaches can provide deeper insights into how manufacturing organizations use statistical and digital information to increase the green competitive advantage.

8. Conclusion

The study focused on improving the pharmaceutical manufacturing companies green competitive advantage through improving data driven decision making process after focusing on various analytical techniques and digital technologies. Data was collected the employees of pharmaceutical companies. The research result shown that biostatistics research, biostatistics attitude, biostatistics knowledge and training, and digital technology significantly contribute to DDDM in pharmaceutical manufacturing companies. The findings further demonstrate that DDDM enhances green decision-making quality, which subsequently supports green competitive advantage by enabling firms to make informed, efficient, and environmentally responsible decisions. The study therefore confirms the importance of integrating statistical capabilities and digital technologies into organizational decision-making to strengthen sustainable business practices and competitive outcomes. Theoretically, the study extends existing knowledge by establishing the link between statistical and digital capabilities, DDDM, green decision-making, and competitive advantage. Practically, the findings encourage manufacturing managers to invest in employee training, statistical capabilities, and digital technologies to improve evidence-based green decisions. For policymakers and industry stakeholders, the findings highlight the importance of promoting digital infrastructure, analytical skills, and data-oriented practices to support sustainable competitiveness in the manufacturing

sector. Research limitations and future direction was also presented at the study end.

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