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Leveraging Data Utilization and Predictive Analytics: Driving Innovation and Enhancing Decision Making through Ethical Governance

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Abstract

Advances in information technology have fueled an exponential increase in the volume and diversity of data generated by organizations and individuals. In this era, Data Science has emerged as a crucial discipline for uncovering hidden patterns within data, thereby facilitating smarter decision-making processes. This paper presents a comprehensive and up-to-date overview of the challenges and opportunities in the application of Data Science, with a particular focus on the PLS (Partial Least Squares) analysis method. The PLS method, implemented through the SmartPLS application, synergizes partial path analysis with partial least squares techniques and has gained prominence as a preferred method for analyzing complex structural models within the field of Data Science. This study delves into the practical applications and benefits of PLS in handling diverse and intricate datasets, and also elucidates the potential obstacles encountered during its implementation. By examining the methodological strengths and addressing the challenges associated with PLS, this paper aims to provide valuable insights for researchers and practitioners seeking to leverage this method and the SmartPLS application for enhanced data analysis and informed decision-making.

Keywords: *Data-driven Innovation, Predictive Analytics, Decision Support Systems*

1. Introduction

The exponential growth in the volume and diversity of data generated by organizations and individuals has significantly transformed the information landscape in recent decades [1]. This phenomenon has propelled Data Science into prominence, aiming to decipher and understand hidden patterns within data to facilitate smarter decision-making [2], [3]. Data Science extends beyond mere data collection and storage; it involves extracting meaningful and valuable insights from vast datasets [4]. Structural modeling stands out as one of the most effective approaches for comprehending the complex relationships among variables in data [5], [6].

Among the various methods available, SmartPLS (Partial Least Squares) has emerged as a highly effective and efficient tool for analyzing complex structural models in Data Science [7], [8], [9]. By integrating partial path analysis with partial least squares techniques, SmartPLS excels in handling diverse and intricate datasets more effectively than traditional methods. This paper provides a comprehensive and up-to-date overview of the challenges and prospects in applying Data Science, with a specific focus on the SmartPLS analysis method [10]. We will explore the practical applications and benefits of SmartPLS in analyzing diverse and complex data, as well as identify the challenges that may arise during its implementation. Additionally, we will discuss the future prospects for the development of data analysis methods using the SmartPLS approach, emphasizing the innovation of more advanced techniques and adaptation to the continuously evolving data landscape [11], [12]. Through this exploration, we aim to offer valuable insights into the critical role of SmartPLS methods in modeling and understanding relationships between variables in Data Science, and provide a forward-looking perspective on the development of data analysis methods to support innovation and enhance decision-making [13].

In the digital era driven by information technology, data has become an invaluable asset for organizations and individuals [14], [15]. The exponential increase in the volume and diversity of data generated daily has reshaped how we understand and utilize information. However, the complexities and diversity of this data demand sophisticated approaches to management, analysis, and interpretation [16], [17]. Addressing these complexities, Data Science has emerged as a discipline dedicated to exploring the potential within data to support more effective and efficient decision-making. Leveraging a variety of statistical, mathematical, and computational techniques, Data Science allows us to uncover hidden patterns, identify trends, and make evidence-based predictions [18], [19]. A deeper understanding of the relationships between variables in data is essential for deriving valuable insights. This is where structural modeling becomes crucial in Data Science. Structural modeling helps us grasp the complexities of variable interactions within a system, enhancing our understanding of these factors. One of the most effective approaches in structural modeling is SmartPLS (Partial Least Squares). SmartPLS is favored by practitioners and researchers due to its ability to efficiently handle diverse and complex data [20]. By combining partial path analysis with partial least squares techniques, SmartPLS overcomes challenges associated with non-normal data distributions and small sample sizes. This paper delves into the role and contributions of SmartPLS in Data Science, offering an up-to-date overview of its applications and advantages in analyzing diverse and complex data [21], [22], [23].

Moreover, we will identify challenges that may be encountered in the implementation of SmartPLS and discuss future prospects for the development of data analysis methods using this approach. Through this exploration, we aim to provide deeper insights into how SmartPLS enhances modeling and understanding of relationships between variables in Data Science. Additionally, we seek to offer a broader view of the future direction for developing data analysis methods to support innovation and better decision-making across various fields [24], [25].

2. Literature Review

The exponential growth in data generation has transformed the landscape of business and research, necessitating advanced methods for data analysis and utilization. Data Utilization (DU) has become a critical aspect in organizations, enabling them to enhance operational efficiency and decision-making processes. Recent studies have emphasized the importance of effective data management practices in harnessing the full potential of data. For instance, Gupta Fu et al. (2023) [26] highlighted that organizations leveraging data-driven decision-making tend to outperform their peers. The ability to collect, store, and analyze vast amounts of data allows organizations to uncover hidden patterns and gain insights that drive innovation and competitive advantage.

Predictive Analytics (PA) plays a pivotal role in this context, offering tools and techniques to forecast future trends based on historical data. The application of predictive analytics in various domains, such as finance, healthcare, and marketing, has demonstrated its potential to improve accuracy in forecasting and risk management. Recent research by Rahardja (2023) [27] argued that predictive analytics is essential for developing robust models that can anticipate future events and support strategic planning. By integrating predictive analytics, organizations can make more informed decisions, reduce uncertainty, and optimize resources. This aligns with the growing emphasis on data-driven innovation (DI), which refers to the process of using data insights to drive the development of new products, services, and business models.

Data-driven Innovation (DI) has been identified as a key driver for organizational success in the modern data economy. Innovation fueled by data insights can lead to the development of new products and services that meet emerging market demands. According to a study by Vieira et al. (2019) [28], companies that prioritize DI are better positioned to adapt to changing market conditions and maintain a competitive edge. The study further suggests that DI not only enhances the product development process but also improves customer engagement and satisfaction by providing more personalized and relevant offerings. This approach underscores the critical role of data in fostering a culture of continuous improvement and responsiveness to market trends.

In addition to driving innovation, data-driven approaches have significant implications for Decision Support Systems (DSS) and Ethical Data Governance (EDG). DSS are designed to assist managers and decision-makers by providing timely, relevant information and analytical capabilities. Studies by Sudaryono et al. 2020 [29] have shown that effective DSS can enhance decision quality, speed, and consistency. Moreover, the ethical governance of data is increasingly critical in ensuring that data is used responsibly and complies with privacy regulations. Researchers such as Handayani et al. (2023) [30] have explored the challenges and frameworks for ethical data governance, emphasizing the need for clear policies and practices to protect data privacy and security. The integration of DU, PA, DI, DSS, and EDG creates a comprehensive framework that not only promotes innovation and efficiency but also ensures that data practices are aligned with ethical standards and regulatory requirements.

3. Method

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data and test the hypotheses. PLS-SEM was chosen for its ability to handle complex structural models with diverse latent variables and indicators. Additionally, this method is suitable for small to medium sample sizes and data that do not meet the normal distribution assumptions. The analysis process begins with data collection through questionnaires designed to measure the research variables. These questionnaires were completed by respondents selected through specific sampling techniques. Once the data was collected, the next step involved preparing the data for analysis by cleaning and verifying its accuracy.

The next step involves constructing the structural model, which consists of the measurement model and the structural model. The measurement model identifies the relationships between latent variables and their indicators, while the structural model depicts the relationships between the latent variables themselves. PLS-SEM is performed using the SmartPLS software. First, the validity and reliability of the constructs are measured by testing convergent and discriminant validity, as well as reliability coefficients. After validating the

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measurement model, the structural analysis is conducted to test the research hypotheses. The results of the structural analysis are interpreted by examining the path coefficients, t-statistics, and R^2 values to determine the strength of the relationships between latent variables. Through this method, the study provides in-depth insights into the complex relationships between the research variables and supports better decision-making based on the analyzed data.

3.1 Model Framework

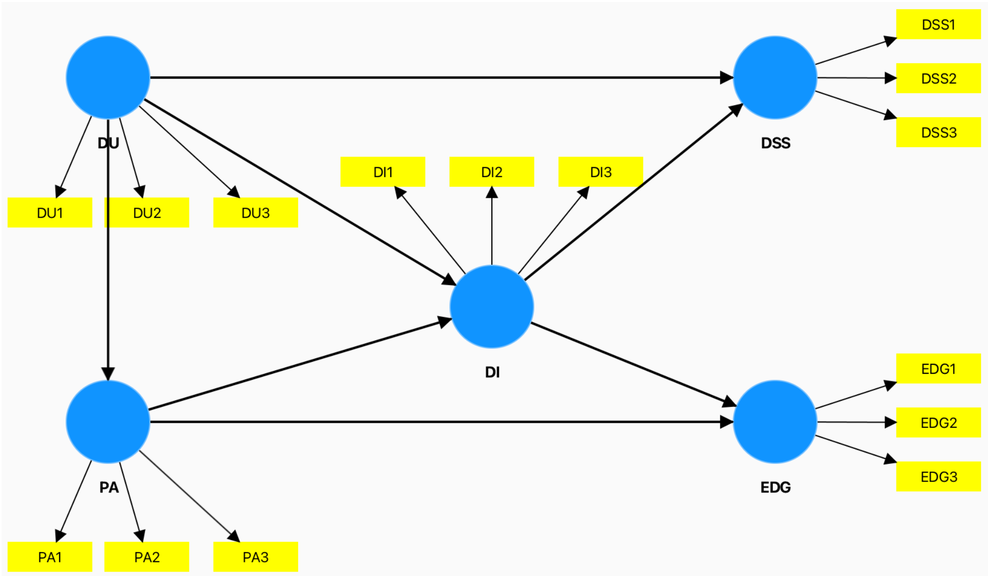

Figure 1. Model Framework

The model framework illustrated in Figure 1 represents the relationships between various constructs in the study. The model includes Data Utilization (DU), Predictive Analytics (PA), Data-driven Innovation (DI), Decision Support Systems (DSS), and Ethical Data Governance (EDG). The framework hypothesizes that Data Utilization (DU) and Predictive Analytics (PA) both have direct influences on Data-driven Innovation (DI). Data-driven Innovation (DI) subsequently impacts Decision Support Systems (DSS) and Ethical Data Governance (EDG). Each construct is measured by specific indicators: DU is measured by DU1, DU2, and DU3; PA by PA1, PA2, and PA3; DI by DI1, DI2, and DI3; DSS by DSS1, DSS2, and DSS3; and EDG by EDG1, EDG2, and EDG3. This framework aims to explore the complex interactions between these constructs, providing a comprehensive understanding of how data utilization and predictive analytics drive innovation, which in turn influences decision support systems and ethical data governance within organizations.

3.2 Responden Profile

The demographic profile of the respondents is summarized in Table 1. The respondents were categorized based on various demographic variables including age, gender, and educational level. The majority of the respondents (81.6%) were between 21 and 30 years old, followed by those over 30 years old (17.6%), and a small portion under 21 years old (0.8%). A higher proportion of the respondents were female (59.2%) compared to male respondents (40.8%). Most of the respondents had completed their education up to the junior high school level (76.4%), while others had primary school education (1.6%), senior high school education (6.8%), diploma (14.8%), bachelor's degree (27.2%), master's degree (6%), and doctoral degree (1.2%)

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Table 1. Demographic Profile of Respondents

Demographic	**Frequency**	**Percentage**
Age		
< 21	2	0.80%
21 – 30	204	81.60%
> 30	44	17.60%
Gender		
Male	102	40.80%
Female	148	59.20%
Educational Level		
Diploma	37	14.80%
Bachelor	68	27.20%
Master	15	6.00%
Doctorate	3	1.20%

3.3 Questionnaire Items

The following section presents the variables and their corresponding statements included in the questionnaire. These variables are designed to capture specific aspects of data utilization within the organization, ranging from operational efficiency to ethical data governance. The statements aim to gather respondents' perceptions and experiences related to data utilization (DU), predictive analytics (PA), data-driven innovation (DI), decision support systems (DSS), and ethical data governance (EDG), providing a comprehensive understanding of how data is leveraged, managed, and governed within the organization.

Table 2. Questionnaire Items

Variable	**Code**	**Statement**
Data Utilization (DU)	DU1	The organization effectively uses collected data to improve operational efficiency.
	DU2	Employees are encouraged to utilize data in their daily tasks and decision-making processes.
	DU3	Data collected is regularly analyzed to identify areas for improvement within the organization.
Predictive Analytics (PA)	PA1	Predictive analytics is used to forecast future trends and outcomes based on historical data.
	PA2	The organization invests in tools and technologies that support predictive analytics.
	PA3	Predictive analytics helps in making informed decisions and minimizing risks.
Data-driven Innovation (DI)	DI1	Data is a key driver of innovation within the organization.
	DI2	New products and services are developed based on insights gained from data analysis.

	DI3	The organization fosters a culture of data-driven experimentation and innovation.
Decision Support Systems (DSS)	DSS1	The decision support systems in place help managers make better and faster decisions.
	DSS2	Employees rely on decision support systems to provide accurate and timely information.
	DSS3	The organization continuously updates its decision support systems to align with current needs.
Ethical Data Governance (EDG)	EDG1	The organization has clear policies and practices in place for ethical data governance.
	EDG2	Data privacy and security are prioritized in all data-related activities.
	EDG3	Employees are trained on the ethical use and management of data.

4. Result
4.1 Path Coefficients

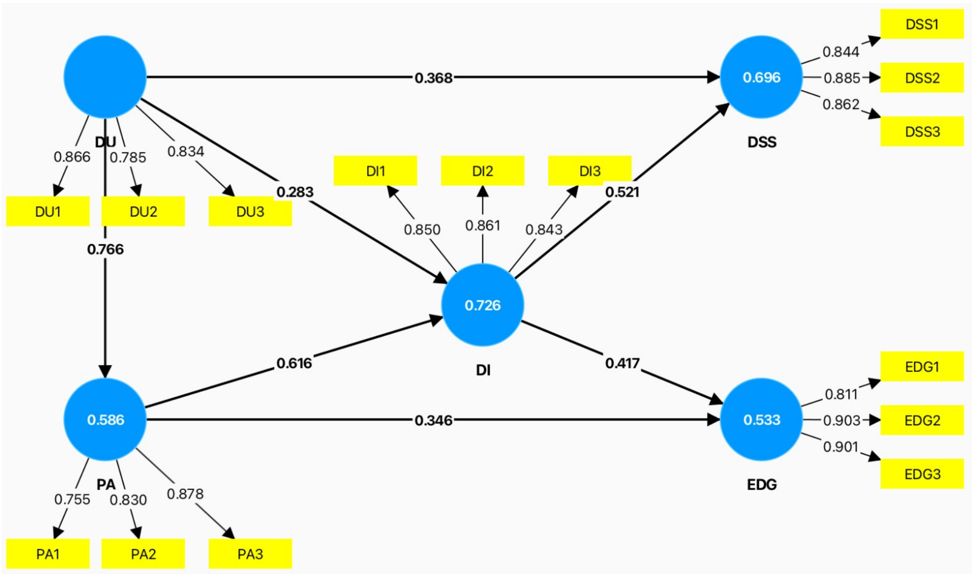

Figure 2. Conceptual model path analysis

The path coefficients illustrated in Figure 2 provide a comprehensive view of the direct relationships between the constructs in the model. These coefficients reflect the strength and direction of the relationships, which are critical for understanding the underlying dynamics of the conceptual framework. The relationship between Data Utilization (DU) and Decision Support Systems (DSS) is positive and significant with a path coefficient of 0.368, indicating that effective data utilization leads to better decision support systems. Similarly, the path coefficient of 0.283 from DU to Data-driven Innovation (DI) suggests a positive impact, albeit to a lesser extent. Predictive Analytics (PA) shows a strong positive influence on DI with a path coefficient of 0.616, highlighting the importance of predictive analytics in driving innovation. Data-driven Innovation (DI) itself has a significant positive impact on both DSS and Ethical Data Governance (EDG), with path coefficients of 0.521 and 0.417, respectively. These results underscore the pivotal role of DI in enhancing decision-making processes and ensuring ethical data practices. Additionally, the strong path coefficient of 0.766 from DU to PA underscores the interdependence between data utilization and predictive analytics. The detailed path coefficients for each relationship are presented in Table 3.

Table 3. Path Coefficients for the Model

Path	**Path Coefficient**
DU -> DSS	0.368
DU -> DI	0.283
PA -> DI	0.616
DI -> DSS	0.521
DI -> EDG	0.417
DU -> PA	0.766
DU1 -> DU	0.866
DU2 -> DU	0.785
DU3 -> DU	0.834
PA1 -> PA	0.755
PA2 -> PA	0.83
PA3 -> PA	0.878
DI1 -> DI	0.85
DI2 -> DI	0.861
DI3 -> DI	0.843
DSS1 -> DSS	0.844
DSS2 -> DSS	0.885
DSS3 -> DSS	0.862
EDG1 -> EDG	0.811
EDG2 -> EDG	0.903
EDG3 -> EDG	0.901

4.2 T-Statistic

The T-Statistic values in the conceptual model path analysis in Figure 2 provide insight into the significance of the relationships between the constructs. The path coefficients and their corresponding T-Statistics indicate the strength and significance of the hypothesized relationships. For example, the path from Data Utilization (DU) to Decision Support Systems (DSS) has a path coefficient of 0.368, which signifies a moderate positive relationship. Similarly, the path from Predictive Analytics (PA) to Data-driven Innovation (DI) has a significant positive relationship with a path coefficient of 0.616. The T-Statistics values greater than 1.96 indicate that the relationships are statistically significant at the 5% significance level, supporting the hypothesized interactions among the constructs. The detailed T-Statistics values for each path are presented in Table 4, which helps in understanding the significance of these relationships in the context of the study.

Table 4. T-Statistic Values for the Model

Path	**T-Statistic**
DU -> DSS	4.701
DU -> DI	3.749
PA -> DI	8.966
DI -> DSS	6.648
DI -> EDG	5.261
DU -> PA	14.741
DU1 -> DU	55.055
DU2 -> DU	27.33
DU3 -> DU	33.647
PA1 -> PA	17.387
PA2 -> PA	24.463
PA3 -> PA	35.152
DI1 -> DI	28.903
DI2 -> DI	30.561
DI3 -> DI	27.997
DSS1 -> DSS	27.634
DSS2 -> DSS	37.76
DSS3 -> DSS	31.159
EDG1 -> EDG	20.064
EDG2 -> EDG	47.229
EDG3 -> EDG	43.893

4.3 Coefficient of Determination

The R^2 represent the proportion of variance in the dependent variables that can be explained by the independent variables in the model. These values provide an indication of the explanatory power of the model. In this study, the R^2 values are used to assess the effectiveness of Data Utilization (DU) and Predictive Analytics (PA) in predicting Data-driven Innovation (DI), as well as the effectiveness of DI in predicting Decision Support Systems (DSS) and Ethical Data Governance (EDG). The R^2 value for Data-driven Innovation (DI) is 0.726, indicating that 72.6% of the variance in DI is explained by DU and PA. This high R^2 value suggests a strong combined influence of data utilization and predictive analytics on driving innovation within the organization. For Decision Support Systems (DSS), the R^2 value is 0.696, meaning that 69.6%

of the variance in DSS can be accounted for by DI and DU, highlighting the significant impact of data-driven innovation and utilization on enhancing decision support systems. Ethical Data Governance (EDG) has an R^2 value of 0.533, indicating that 53.3% of the variance in EDG is explained by DI, underscoring the role of innovation in promoting ethical data practices.

Table 5. R^2 Values for the Model

Dependent Variable	**R^2 Value**
Data-driven Innovation (DI)	0.726
Decision Support Systems (DSS)	0.696
Ethical Data Governance (EDG)	0.533

5. Conclusions

. This study has provided a comprehensive examination of the interplay between Data Utilization (DU), Predictive Analytics (PA), Data-driven Innovation (DI), Decision Support Systems (DSS), and Ethical Data Governance (EDG). The findings highlight the critical role of DU and PA in fostering DI, which subsequently enhances DSS and EDG within organizations. The model demonstrates that effective data utilization and predictive analytics are pivotal in driving innovation, leading to improved decision-making processes and adherence to ethical standards. The significant path coefficients and R^2 values underscore the strong relationships among these constructs, affirming their interdependence and collective impact on organizational performance.

The path analysis revealed that DU and PA significantly contribute to DI, with path coefficients of 0.283 and 0.616, respectively. DI, in turn, has a notable positive effect on both DSS and EDG, with path coefficients of 0.521 and 0.417. These results indicate that fostering an environment where data is effectively utilized and predictive analytics are integrated into decision-making processes can lead to substantial improvements in innovation and governance practices. Moreover, the strong explanatory power of the model, as indicated by the R^2 values, validates the importance of these factors in driving organizational success.

For future research, it would be beneficial to explore additional variables that may influence the relationships identified in this study. Variables such as organizational culture, technology adoption readiness, and regulatory compliance could provide deeper insights into the dynamics of data-driven innovation and governance. Additionally, longitudinal studies could help in understanding the long-term effects of DU, PA, DI, DSS, and EDG on organizational performance. Expanding the research to different industry contexts and geographical regions could also offer a more comprehensive view of how these constructs interact across various settings. Future studies should continue to build on these findings to develop more robust models and frameworks that can guide organizations in leveraging data for sustainable growth and ethical governance.

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