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Integrating Data Science into Total Quality Management and its Effects on Enterprises

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Abstract: ***This investigation examines the integration of Data Science (DS) into Total Quality Management (TQM) processes within enterprises, focusing on DS's impact on quality and operational efficiency. Jordanian enterprises often face considerable challenges in maintaining high standards of quality and efficiency due to limited resources. This study examines how DS affects key Total Quality Management (TQM) metrics, including defect rates, operational efficiency, customer satisfaction, inventory management, and downtime, across varying degrees of DS adoption. This study used a quantitative, correlational research approach, drawing on data from structured surveys and operational records from businesses classified as having low, moderate, or high DS integration. The ANOVA, t-tests, and correlation analyses indicated significant statistical improvements across all metrics associated with higher levels of Data Science (DS) integration. Specifically, DS-driven quality control was correlated with lower defect rates, improved production efficiency, and greater customer satisfaction. Additionally, using DS in predictive maintenance and inventory management reduced waste and downtime. These results imply that incorporating DS into Total Quality Management (TQM) offers businesses strategic advantages, such as improved quality, operational resilience, and enhanced competitiveness. The study concludes that integrating DS into TQM processes is a promising approach for companies aiming for sustainable growth in a technology-focused market.***

Keywords: ***Data Science, Total Quality Management, Enterprises***

Nomenclature:
DS: Data Science
TQM: Total Quality Management
SPSS: Statistical Package for the Social Sciences
AI: Artificial Intelligence
MSMEs: Micro, Small and Medium-Sized Enterprises

I. INTRODUCTION

In today's competitive market, Jordanian Enterprises face mounting pressure to deliver premium products and services efficiently while managing finite resources [1]. Total Quality Management (TQM) is a methodical framework designed to enhance organisational processes and foster customer satisfaction, making it an indispensable strategy for Enterprises. Nevertheless, implementing TQM effectively remains a formidable challenge, as entities often face financial and operational impediments stemming from limited resources that hinder the adoption of sophisticated quality management systems [2].

In recent years, Data Science (DS) has emerged as a paradigm-shifting technology, poised to transform Total Quality Management (TQM) practices by leveraging automation, augmenting decision-making capabilities, and providing prescriptive analytics that optimise quality control and operational efficiency. [3] The integration of Data Science (DS) into quality management spans a multifaceted array of functionalities, comprising real-time surveillance, anomaly detection, predictive maintenance, and customer sentiment analysis, thereby facilitating a holistic approach to quality optimization [4]. These functionalities enable Jordanian Enterprises to overcome conventional Total Quality Management (TQM) limitations by reducing human error, streamlining resource allocation, and improving agility in response to market fluctuations, fostering a more adaptive and resilient quality management framework [5]. Studies indicate that DS can reduce defect rates by up to 30% in production environments, significantly enhancing product quality and lowering costs associated with rework and scrap [1]. Moreover, the application of Data Science (DS) in inventory management and predictive maintenance enables Jordanian Enterprises to optimise resource utilisation, thereby minimising waste and downtime, which is paramount for organisations striving to maintain streamlined operations and achieve peak productivity, while fostering a culture of operational excellence.

II. LITERATURE REVIEW

A. Total Quality Management (TQM) in Enterprises

Total Quality Management (TQM) is a holistic management paradigm centred on continuous improvement, customer focus, and error minimisation across an organisation's entire operational spectrum. TQM emphasises a holistic view of quality, involving all members of an organisation in improving processes, products, services, and the culture in which they work [6]. Originally conceived for large-scale industrial corporations, the principles of Total Quality Management (TQM) have been successfully adapted and implemented by Jordanian Enterprises to elevate their quality benchmarks and augment their competitive edge [7].

Despite its benefits, implementing TQM in enterprises often faces significant challenges.

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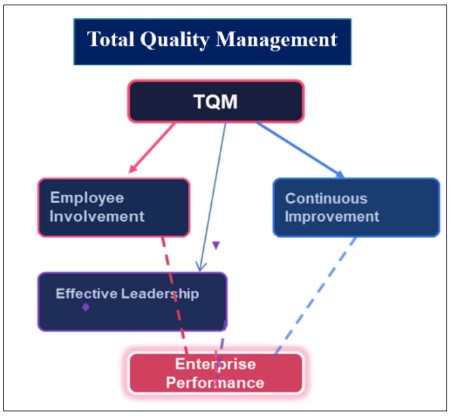
Research indicates that financial constraints, lack of technological infrastructure, and insufficient workforce capabilities can hinder effective TQM implementation [2]. Moreover, Jordanian Enterprises frequently struggle to adopt sophisticated quality management systems because of limited resources, which can lead to reactive rather than proactive quality management practices [8].

Drawing upon established TQM frameworks, the researcher proposes a novel TQM model (Figure 1). This conceptual framework integrates three pivotal elements that collectively impact stakeholders, namely: employee engagement, strategic leadership, and ongoing enhancement.



[Fig.1: Suggested TQM Model]

Efficacious leadership within an organisation is a crucial determinant and fundamental prerequisite for successfully implementing the Total Quality Management (TQM) philosophy. A resolute commitment to this philosophy requires organisational leaders to develop a strategic plan with clearly defined objectives and methods that prioritise long-term profitability. To facilitate the effective execution of TQM, management must undertake several key responsibilities, including: (a) generating momentum, (b) furnishing the requisite resources and capabilities, (c) orchestrating a sustained and adaptive transformation of the organisational structure and culture, (d) proactively anticipating and mitigating potential challenges, (e) making informed, data-driven decisions, (f) fostering a collaborative and coordinated team environment, and (g) encouraging innovative contributions from individuals and groups to enhance product quality and optimise productivity. These essential management tasks collectively form the nucleus of a successful TQM adoption strategy. [9]

The concept of continuous improvement is rooted in a fundamental axiom: that every aspect of an organisation is inherently susceptible to perpetual refinement. This principle extends beyond products and services, encompassing the entire organisation, its processes, and all related facets. [10]

As a cornerstone of Total Quality Management (TQM), employee involvement requires transparent plans, policies, and objectives that empower individuals to understand their distinct contributions to implementing this philosophy successfully. By engaging every organisational member in collaborative teamwork, problem-solving, decision-making, and quality-improvement initiatives, organisations instil a strong sense of purpose and effectiveness, as individuals see their work as vital to achieving organisational goals. This, in turn, fosters a deep-seated loyalty and affinity among employees, as they become increasingly invested in the organisation's success.

B. The Role of Data Science (DS) in Enhancing TQM

Data Science (DS) has emerged as a transformative technology with the potential to revolutionise TQM practices in enterprises. DS involves using advanced analytical methods, statistical techniques, and predictive modelling to extract meaningful insights from vast amounts of data. These capabilities empower organisations to optimise processes such as inventory management and operational efficiency, offering significant benefits for quality control and decision-making. [11] This integration highlights the essential role of DS in modernising TQM practices and aligning them with data-driven strategies.

The integration of Data Science (DS) into quality management spans a broad spectrum of functionalities, including real-time surveillance, anomaly detection, predictive maintenance, and customer sentiment analysis [4]. By leveraging these capabilities, Jordanian Enterprises can mitigate traditional Total Quality Management (TQM) challenges by reducing human fallibility, streamlining resource allocation, and increasing agility in responding to market fluctuations [5]. For example, predictive analytics can help organisations anticipate potential quality issues before they arise, allowing for timely DS

A data corpus is a structured collection of data used for analysis and machine learning, providing a foundation for insights and model training [13]. Effective

Data analysis involves applying statistical techniques to explore and interpret this corpus, allowing researchers to identify patterns, relationships, and anomalies that inform decision-making [14]. Subsequently,

Machine learning algorithms use the insights gained from the analysis to develop predictive models, enabling automation and improving accuracy in applications ranging from finance to healthcare. Together, these components create a cohesive framework for leveraging data to drive innovation and informed choices. [12]

C. Impact of DS on TQM Metrics

DS plays a critical role in predictive maintenance by minimising operational disruptions and enhancing system reliability. As Tan, Zhang, and Chen (2022) emphasise, DS-driven predictive maintenance enables organisations to anticipate equipment failures and intervene promptly. This approach reduces downtime, optimises resource allocation, and aligns maintenance practices with Total Quality Management (TQM) objectives.

D. Challenges of DS Adoption in TQM

Despite the potential benefits of incorporating DS into TQM, Jordanian Enterprises face several challenges in its adoption. As Tan, Zhang, and Chen (2022) note, cost remains a significant barrier, as implementing DS technologies often requires substantial upfront investments. Additionally, the need for skilled personnel and robust digital infrastructure adds to the complexity of DS adoption. Addressing these challenges is critical for enabling organisations

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to fully realise the advantages of integrating DS into TQM. Additionally, the lack of digital infrastructure and skilled personnel further complicates integrating DS into existing TQM processes (Singh & Verma, 2021).

Data Science (DS) and Total Quality Management (TQM) are intricately linked to organisational performance. Both DS and TQM consider several factors. In DS, key components include the data corpus, data analysis, and machine learning techniques. On the other hand, TQM encompasses elements such as leadership commitment, strategic planning, continuous improvement, customer orientation, process emphasis, employee engagement, training and development, and rewards and recognition. [15] Moreover, performance measurement is crucial to the overall organisational process.

III. RESEARCH METHODOLOGY

This study investigates the impact of integrating Data Science (DS) into Total Quality Management (TQM) processes within Jordanian enterprises, focusing on quality enhancement and operational efficiency [16]. The methodology outlines the research design, variables, data collection, analysis techniques, and ethical considerations.

A. Research Design

The study adopts a quantitative, correlational research design to examine the relationship between DS integration levels and TQM outcomes. This design is appropriate for exploring non-experimental settings, enabling the measurement of relationships without direct intervention. [17] Jordanian Enterprises were categorised into three levels of DS integration: Low, Moderate, and High, allowing for comparative analysis of TQM metrics.

B. Research Hypotheses

i. Research Variables

The primary independent variable of interest is Data Science (DS), which is further decomposed into the following constituent variables:

- Data Corpus.
- Data Analysis.
- Machine Learning Algorithms

The second primary independent variable is Total Quality Management (TQM), which is further divided into the following components:

- Effective leadership.
- Continuous improvement.
- Employee involvement

The main dependent variable is enterprise performance, Perception towards Performance

ii. Research Hypotheses

This study examines two primary hypotheses, each broken down into several sub-hypotheses. In general, a hypothesis is a critical component of research, serving as a tool to help researchers focus on the central topic. It also represents an alternative assumption that allows for the exploration and testing of its logical or empirical implications. Consequently, the hypothesis is a key instrument in research. asserted that the hypothesis helps direct the researcher in exploring answers to the provisional generalisations they have formulated. [18], [19].

In this context, the emphasis is on Data Science (DS) and Total Quality Management (TQM). These two modern concepts are essential for the educational management process and its results.

This study proposes two hypotheses that need to be justified. Fig.2 illustrates their structure and relationship with the primary variables of the current research.

i. The First Hypothesis

H1: There is a significant relationship between DS and TQM. This hypothesis is subdivided into the following sub-hypotheses.

- H.1.1 There is a significant relationship between the Data Corpus of DS and effective leadership.
- H.1.2 There is a significant relationship between the Data Corpus of DS and continuous improvement.
- H.1.3 There is a significant relationship between the DS Data Corpus and employee involvement.
- H.1.4 There is a significant relationship between Data Analysis of DS and effective leadership.
- H.1.5 There is a significant relationship between Data Analysis of DS and continuous improvement.
- H.1.6 There is a significant relationship between Data Analysis of DS and employee involvement.
- H.1.7 There is a significant relationship between Machine learning algorithms and effective leadership.
- H.1.8 There is a significant relationship between Machine learning algorithms and continuous improvement.
- H.1.9 There is a significant relationship between machine learning algorithms and employee involvement.

ii. The Second Hypothesis

H2: There is a significant effect of the integration of DS and TQM in enterprises

[Fig.2: Structure and Relationship with the Primary Variables]

C. Data Collection and Sampling Technique

Data collection in this study employed a mixed-methods approach to ensure a thorough understanding of DS integration within TQM processes. Structured questionnaires were distributed to managers and

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heads of TQM departments to gather insights regarding the extent of DS adoption, customer satisfaction levels, and inventory management practices. These surveys offered a standardised method for capturing both subjective and operational perspectives across a variety of enterprises. To complement the surveys, operational records were analyzed to obtain objective metrics, including defect rates, production times, and downtime durations. This approach utilised enterprise-provided data to ensure accuracy and mitigate potential biases related to self-reported information (Creswell & Creswell, 2022).[20] Furthermore, secondary data from industry reports and published statistics were incorporated to contextualise the findings, enabling standardised comparisons across Jordanian Enterprises and enhancing the depth and consistency of the analysis of TQM outcomes.

The study employed stratified random sampling to ensure representation across Jordanian Enterprises with varying levels of DS adoption, categorised as low, moderate, and high. Stratifying the sample by DS adoption level ensured the study captured data from all levels of DS integration, which is critical for hypothesis testing [21]. The sample size was determined through power analysis to ensure statistical validity, with an expected sample size of approximately 100 Enterprises, evenly distributed across the three DS adoption levels. This method ensures robust and reliable results [22]. The inclusion criteria focused on Jordanian Enterprises that have integrated DS within their TQM processes and operate in sectors where TQM is standard practice, such as manufacturing, retail, and logistics [23]. Jordanian Enterprises without DS adoption, or those using DS for purposes other than TQM (e.g., DS in marketing), were excluded to maintain focus on DS-driven TQM outcomes [6].

D. Data Analysis Techniques

To evaluate the hypotheses, a combination of statistical methods will be applied to evaluate the relationships between DS integration and various TQM outcomes. Descriptive statistics, including mean, median, and standard deviation, will provide a general overview of the key variables and offer insights into data distribution across different levels of DS adoption [24]. The Analysis of Variance (ANOVA) will be used to assess whether statistically significant differences exist in TQM outcomes, such as defect rates, customer satisfaction, and production times, across Jordanian Enterprises with varying levels of DS adoption (Low, Moderate, High). ([25]). To examine the strength and direction of relationships between DS integration and operational metrics such as defect rates and downtime, Pearson's correlation coefficient will be calculated (Schobert, Boer & Schwarte, 2018). Furthermore, multiple regression analysis will be conducted to evaluate the extent to which DS adoption can predict TQM metrics, such as customer satisfaction and inventory wastage, while controlling for potential confounding variables, including Jordanian enterprises' size and industry type (Magzoub, E. H., 2021). These analyses will be performed using statistical software such as SPSS or R to ensure reliable, reproducible results. The findings will be interpreted at a 95% confidence level, with a significance threshold set at $p < 0.05$, to assess the statistical validity of the results (Pallant, 2020). Potential limitations include variability in data quality across Jordanian Enterprises and limited generalizability due to the sample's homogeneous nature. Future research may consider longitudinal studies to explore the long-term impact of DS on TQM outcomes (Palumbo, R., & Douglas, A., 2024).

E. The Quantitative Data Analysis of Respondent Perceptions in Enterprises.

This section presents the analysis of responses collected from various Jordanian enterprises using a five-point Likert scale. Data were processed using SPSS, organised by statement rank order, and analysed using frequency, mean, and standard deviation. Pearson correlation coefficients were then computed to test the research hypotheses, and multiple regression analysis was used to assess the combined effect of Data Science (DS) and Total Quality Management (TQM) on enterprise performance.

- ***The Perception of Data Science DS Data Corpus***

The mean scores for the ten statements related to the DS Data Corpus (statements 1–10) ranged from 3.86 to 3.91, with standard deviations between 0.97 and 1.13. These values indicate that respondents generally agreed with the statements, as the mean scores approached 4.00 on the Likert scale (Agree). The overall mean for this construct was 3.88 (SD = 1.05), reflecting a positive perception toward the DS Data Corpus among enterprise respondents.

Table I: Overall Descriptive Statistics for DS Data Corpus (Statements 1–10)

Variable	Mean	Standard deviation
DS Data Corpus 1-10	3.88	1.05

- ***The Perception of Data Science (DS) Data Analysis***

For the eight statements concerning DS Data Analysis (statements 11–18), mean scores ranged from 3.77 to 4.01, with an overall mean of 3.89 (SD = 0.35). These results indicate consistent agreement among respondents regarding the role and effectiveness of data analysis techniques in supporting quality-related decision-making.

Table II: Overall Descriptive Statistics for DS Data Analysis (Statements 11–18)

Variable	Mean	Standard deviation
DS Data Analysis 11-18	3.89	0.35

- ***The Perception of Data Science DS Machine Learning Algorithms***

The twelve statements related to Machine Learning Algorithms (statements 19–30) yielded mean scores between 3.88 and 3.96, with an overall mean of 3.92 (SD = 0.30). This indicates a strong positive perception of using machine learning techniques to enhance TQM processes.

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Table III: Statistics of the Overall Ranks for Machine Learning Algorithms (Statements 19-30)

Variable	Mean	Standard deviation
DS Machine Learning Algorithms 19-30	3.92	0.3

The aggregate mean for all 30 DS-related statements was 3.90 (SD = 0.56), confirming an overall positive perception of Data Science integration within enterprises.

Table IV: Statistics of the Overall Ranks for DS (Statements 1-30)

Variable	Mean	Standard deviation
DS Overall 1-30	3.9	0.56

F. The Perception towards TQM

- ***Effective Leadership***

The seven statements regarding effective leadership (statements 31–37) had mean scores ranging from 3.91 to 3.99, with an overall mean of 3.95 (SD = 0.83), indicating strong agreement with leadership's role in supporting TQM.

Table V: Statistics of the Overall Ranks for Effective Leadership (Statements 31 - 37)

Variable	Mean	Standard deviation
Effective Leadership 31-37	3.95	0.83

- ***Continuous Improvements***

For the five statements addressing continuous improvement (statements 38–42), mean scores ranged from 3.85 to 3.89, with an overall mean of 3.87 (SD = 0.50), reflecting positive perceptions toward ongoing process enhancement.

Table VI. Overall Descriptive Statistics for Continuous Improvement (Statements 38–42)

Variable	Mean	Standard deviation
Continuous Improvement 38- 42	3.87	0.5

- ***Employee Involvement***

The eight statements concerning employee involvement (statements 43–50) produced mean scores between 3.86 and 3.89, with an overall mean of 3.87 (SD = 0.35), indicating strong agreement with the importance of engaging employees in quality initiatives.

Table VII: Statistics of the Overall Ranks for Employee Involvement (Statements)

Variable	Mean	Standard deviation
Employee Involvement 43-50	3.87	0.35

The overall mean for all TQM-related statements (31–50) was 3.90 (SD = 0.30), confirming a positive perception toward TQM practices across Jordanian enterprises.

Table VIII: Statistics of the Overall Ranks for TQM (Statements)

Variable	Mean	Standard deviation
TQM Overall 31-50	3.9	0.3

- ***Hypothesis Testing: Correlation Analysis***

To examine the relationships between DS components and TQM dimensions, Pearson correlation coefficients were computed. The results are summarised below.

Pearson correlation coefficients were computed to examine the relationships between DS components and TQM dimensions. The results are summarised below.

G. Correlation between DS Data Corpus and TQM Dimensions

The DS Data Corpus showed a weak to moderate positive correlation with:

- Effective Leadership: $r = 0.370$, $p < 0.001$
- Continuous Improvement: $r = 0.283$, $p < 0.01$
- Employee Involvement: $r = 0.369$, $p < 0.001$

These findings indicate that as the use of structured data corpora increases, TQM practices tend to improve. Consequently, null hypotheses H1.1, H1.2, and H1.3 are rejected.

Table IX: Correlation Coefficient of DS Data Corpus with TQM Effective Leadership, Continuous Improvement, Or Employee Involvement in Jordanian Enterprises (N=50)

		Effective Leadership	Continuous Improvement	Employee Involvement
DS Data Corpus	Pearson (r)	0.370**	0.283*	0,369**
	Significance (2-tailed)	0	0,001	0
Testing relevant hypothesis		H1.1 is rejected	H1.2 is rejected	H1.3 is rejected

Note: **P<0.001, P<0.01

- ***Correlation between DS Data Analysis and TQM Dimensions***

DS Data Analysis demonstrated a weak to moderate positive correlation with:

i. Effective Leadership: $r = 0.385$, $p < 0.001$
ii. Employee Involvement: $r = 0.350$, $p < 0.001$
iii. Continuous Improvement: $r = 0.399$, $p < 0.001$

Thus, null hypotheses H1.4, H1.5, and H1.6 are rejected

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Table X: Correlation Coefficient of DS Data Analysis with TQM Effective Leadership, Employee Involvement, and Continuous Improvement in the Jordanian Enterprises (N=50)

		Effective Leadership	Employee Involvement	Continuous Improvement
DS Data Analysis	Pearson (r)	0.385**	0.350*	0.399**
	Sig. (2-tailed)	0	0	0
Testing relevant hypothesis		H1.4 is rejected	H1.5 is rejected	H1.6 is rejected

- ***Correlation between DS Machine Learning Algorithms and TQM Dimensions***

Machine Learning Algorithms also showed a weak to moderate positive correlation with:

i. Effective Leadership: $r = 0.390$, $p < 0.001$
ii. Continuous Improvement: $r = 0.301$, $p < 0.01$
iii. Employee Involvement: $r = 0.354$, $p < 0.001$

Therefore, null hypotheses H1.7, H1.8, and H1.9 are rejected.

Table XI: Correlation coefficients between DS Machine Learning Algorithms and TQM Effective Leadership, Continuous Improvement, and Employee Involvement in Jordanian Enterprises (N=50)

		Effective Leadership	Continuous Improvement	Employee Involvement
DS Machine Learning Algorithms	Pearson r	0.390**	0.301*	0.354**
	Sig. (2-tailed)	0	0	0
Testing relevant hypothesis		H1.7 is rejected	H1.8 is rejected	H1.9 is rejected

- ***4.7.4 Overall Correlation between DS and TQM***

The overall correlation between DS (as a composite construct) and TQM was moderate and positive ($r = 0.580$, $p < 0.001$), suggesting a meaningful association between the two constructs. Consequently, null hypothesis H1 is rejected.

Table XII: Overall Correlation between DS and TQM (N = 50)

Variable	TQM
DS	Pearson r = 0.580**
Hypothesis	H1 Rejected

H. Regression Analysis: Effect of DS and TQM on Enterprise Performance

A multiple linear regression analysis examined the combined effect of DS and TQM on Enterprise Performance (EP). The model was statistically significant, $F(2, 47) = 36.11$, $p < 0.001$, and explained approximately 26.5% of the variance in enterprise performance ($R^2 = 0.265$, Adjusted $R^2 = 0.245$). The regression equation is:

$$EP = 0.229 + 0.519(DS) + 0.418(TQM)$$

Both predictors were significant:

- DS: $\beta = 0.519$, $t = 3.711$, $p < 0.001$
- TQM: $\beta = 0.418$, $t = 4.860$, $p < 0.001$

These results indicate that both DS and TQM independently and significantly contribute to enterprise performance. Therefore, we reject the null hypothesis H2.

Table XIII: Multiple Regression of DS and TQM on Enterprise Performance (N = 50)

Predictor	Unstandardized B	Standardized β	t	Sig
Constant	0.229	–	0.51	0.618
DS	0.519	0.482	3.711	0
TQM	0.418	0.39	4.86	0
Model Summary				
R		0.514		
R^2		0.265		
Adjusted R^2		0.245		
F		36.11**		

** $p < 0.001$

I. Limitations of the Study

This study acknowledges several limitations. Variability in data quality across enterprises may affect the reliability of findings. The sample homogeneity limits the generalizability of results to a broader range of industries. Moreover, the cross-sectional design restricts the ability to infer causality or capture long-term dynamics of DS–TQM integration.

IV. CONCLUSION

The analysis of respondent perceptions of Data Science (DS) and Total Quality Management (TQM) across various Jordanian Enterprises reveals a positive outlook, emphasising DS's potential to transform TQM practices.

A. Key Findings Include

Positive Perceptions of DS: Jordanian Enterprises demonstrated favourable views toward DS initiatives, with average scores ranging between 3.879 and 4.002, highlighting its importance in data-driven decision-making.

Effective Leadership and Continuous Improvement: Leadership and continuous improvement were highly rated, with means between 3.85 and 4.03, reflecting their critical role in fostering a DS-supportive environment.

Correlation Insights: Strong positive correlations were observed between DS and TQM elements, such as effective leadership and employee involvement, indicating DS's capacity to enhance TQM practices.

Overall Impact: Regression analysis confirmed that DS and TQM significantly influence enterprise performance, explaining 26.6% of the variation in outcomes.

The findings highlight the transformative potential of integrating Data Science (DS) into Total Quality Management (TQM). Beyond improving operational metrics such as defect reduction and customer satisfaction, integrating DS establishes a data-driven culture that aligns with TQM principles of continuous improvement and proactive decision-making. This synergy fosters resilience and adaptability within enterprises, enabling them to respond effectively to dynamic market demands.

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The statistical analyses further validate the pivotal role of DS in optimising key TQM practices, suggesting that Jordanian Enterprises that strategically invest in DS capabilities are more likely to achieve sustainable growth and competitive advantage. These insights underline the necessity for Jordanian Enterprises to bridge technological and skill gaps to fully leverage the benefits of DS in TQM, paving the way for a future where data-driven strategies are central to quality and operational excellence. In conclusion, this study underscores the strategic value of integrating DS into TQM, enabling Jordanian Enterprises to enhance performance and competitiveness.

B. Further Research

Future studies could explore the long-term impacts of integrating Data Science (DS) into Total Quality Management (TQM) through longitudinal research, providing deeper insights into how DS-driven quality management practices evolve. Additionally, industry-specific analyses could uncover how DS adoption varies across sectors such as manufacturing, healthcare, and retail, offering tailored strategies for effective implementation. Addressing barriers to DS adoption, including technological constraints and skill gaps, would further clarify how Jordanian Enterprises can overcome these challenges. Expanding the sample to include diverse Jordanian Enterprises globally could also improve the generalizability of findings and offer more comprehensive insights into the relationship between DS and TQM.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

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- **Funding Support:** This article has not been funded by any organisations or agencies. This independence ensures that the research is conducted objectively and without external influence.
- **Ethical Approval and Consent to Participate:** The data provided in this article are exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The resources in this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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