Evaluating the Mediating Effect of Data Analytics Capability on SMEs' Service Performance: Jordan's Case Study

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Abstract: - This study examines how competitive pressure, social influence, and customer trust affect service performance in Jordanian IT small and medium-sized enterprises (SMEs), with data analytics capability as a mediating variable. Using a quantitative design, data were collected from 352 employees across 12 IT SMEs and analysed via PLS-SEM. Results show that competitive pressure exerts the strongest direct effect on service performance, while social influence has a modest but significant direct effect. Customer trust shows no significant direct impact. Data analytics is confirmed as a powerful predictor of service performance and plays a significant mediating role across all three factors: partially mediating the effects of competitive pressure and social influence, and fully mediating the effect of customer trust. These findings underscore the critical role of data analytics in converting market pressures and relational assets into tangible service outcomes, with practical implications for SME digital capability development.

Key-Words: - Competitive Pressure, Social Influence, Customer Trust, Data Analytics, Service Performance, IT SMEs, Jordan.

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1 Introduction

SMEs contribute significantly to the fast development and growth of economically qualified countries around the world. Though important, SMEs suffer a lot of challenges which impede their performance, [1], [2].

Many times, the issue is not in the resources, but a gap between expected and actual performance. That is because small and medium-sized enterprises (SMEs) often find it difficult to integrate technological advancements across their entire business strategy, [3]. In addition, a number of small to medium enterprises (SMEs) struggle to handle all the challenges of implementing new technologies and keep abreast with a rapid technological redevelopment. These challenges make it more difficult to compete successfully in the domestic and foreign markets by small and medium-sized enterprises (SMEs). This affects their ability to expand and provide more customer services, [4].

Jordanian IT SMEs provide software and equipment services and goods and profit from digital infrastructure, tax exemptions, laws, and competent staff. Due to their complexity, tender regulations in the sector are difficult and inflexible to apply to information technology systems, according to other research, [5]. The State of the Country report [6] found hundreds or thousands of poor-quality technical programs in the Jordanian market that lack oversight and credibility in product quality and services before and after sales.

Overall, this study will explore the relationship between Competitive Pressure, Social Influence, and Customer Trust with the SMEs' service performance, together with the mediating effect of Data Analytics.

2 Literature Review

2.1 Competitive Pressure and SMEs Service Performance

The correlation between Competitive Pressure in data analytics within Small and Medium Enterprises (SMEs) and Performance centres on how external market forces and pressure from competitors influence the favourable outcomes of projects in these businesses, driving them to adopt data analytics tools and techniques to stay competitive.

Competitive pressure refers to the “pressure felt by the competitors within the same industry”. In previous literature, it is argued that competitive pressure affects technology adoption when a firm identifies that this adoption of technology leads towards competitive advantage and, ultimately, firm performance. The general view held by all economists is that competition increases the chances of adoption of an innovation. It was argued in the literature that IT adoption had affected the competition in three ways: by changing the rules of competition, industry structure, and by providing new business methods in the industry. Previous studies have shown that competition intensity is positively influenced by the degree of e-commerce adoption. Therefore, the present study has created a missing link between competitive pressure and firm performance through the use of e-commerce, [7].

Competitive pressure is the level of competitive atmosphere in the industry in which the company operates. The intensity of competition is defined as market factors that affect the level of competition measured by the number of similar companies in the same industry, product competition in the market, resulting in changes in market share from the competition, the level of price manipulation, contractual agreements between customers and competitors, changes in government regulations and policies, intensity price competition, competition product intensity (differentiation), product promotion, and channel distribution. Organisations are likely to adopt innovation because of intense competition in a competitive environment, [8]

Organisations will distribute resources to offer innovative products or services to react to competitors in a competitive environment. Innovation is the application of knowledge to produce new knowledge. Innovation capability enables companies to implement appropriate process technology to develop new products to meet market needs and eliminate the threat of competitiveness. Innovations are important for the sustainability of excellence. Every new idea that generates added value by application in practice can be called innovation. Businesses that operate in complex environments pose a challenge for business leaders in adapting to changes in the environment, [9].

Competition pressures affect performance in various ways. The sharp nature of competition will be a serious problem for companies, as the business environment has undergone a change marked by uncertainty and the intensity of increased competition, [10]. Companies will try to survive the complexity of the environment through adaptation. Some previous research that discusses the effect of competitive pressures on business performance is [11]. The research shows that competitive pressures affect business performance. Therefore, one could hypothesize the following:

H1: Competitive Pressure has a significant effect on SMEs' service performance.

2.2 Social Influence and SMEs Service Performance

The interaction between Social Influence and data analytics in terms of the project success in the context of Small and Medium Enterprises (SMEs) is based on the factors in which the effect of opinions, interactions and support with colleagues and stakeholders are involved in the positive success of projects in these companies.

Social Influence entails the influence that the colleagues, peers and stakeholders have over the attitudinal and behavioural changes concerning data analytics. It is the power of collective persuasion, encouragement and collaboration, a social force, the success of people within the boundary of an organisation who induce one another to manifest the use of data analytics in their projects.

Service level of SMEs refers to the method employed in attaining planned project goals within small- and medium-sized enterprises. Going by a checklist may be a simple way which can help in achieving project milestones, deliverables & align its scope with business outcomes.

You also find that amongst SMEs, positive social influence, e.g., use of data analytics in performance, has a higher likelihood. In no other way will data analytics be promoted through colleagues & stakeholders’ action and collaboration, knowledge sharing, etc., that ultimately boost motivation as a team, teamwork and overall performance of the project. In turn, this will enable them to work together and form a data-driven decision-making culture that feeds excellence back into the project.

Conversely, without social influence or even resistance, the data analytics will impede project progress. Colleague scepticism can be an obstacle to integrating and deploying data analytics tools, putting the enhancement of Performance Scores in Jeopardy.

Social Influence on SME Performance drives home the importance of creating a positive working culture that could facilitate data analytics adoption. Open communication, knowledge transfer, and evolving a culture that makes both colleagues and stakeholders inspire each other to use data analytics are something SMEs should aim for. When social influence aligns with the adoption of data analytics, the likelihood of Performance is significantly enhanced, and the organisation can fully harness the benefits of data-driven decision-making in its projects. Therefore, one could hypothesise the following:

H2: The Social Influence of data analytics has a significant effect on SMEs' service performance.

2.3 Customer Trust and SMEs Service Performance

Customer trust is an environmental factor that is the major determinant of the performance of small and medium-sized businesses (SMEs) in Jordan. Trust is one of the most important relationship variables that influence the overall satisfaction, loyalty, and long-term partnerships as it is the key to the interactions of companies between each other and their customers. By building and sustaining the trust of business partners, a positive corporate environment where customers have confidence in the quality of services they get can be created. Here's one method for doing it. The customer trust also affects the customer retention rate in the firm, the level of performance (i.e. customer services) and the status of the firm which affect the extent to which the firm success in offering the services in the small and medium-size enterprises (SMEs).

Correlation between customer trust and service performance can also be demonstrated by the ways businesses treat their customers, by being transparent and honest with them as well as correcting any issues that may arise in the process. Perhaps SMEs can benefit from a strategy and culture of exceeding their customers' expectations and improving the quality of service delivery if they focus on building trust by delivering consistently reliable services with transparent communication. It is a trust-based strategy which when used by small and medium-sized enterprises (SMEs) can assist them to compete in the market as long as they can still react swiftly and in a holistic manner to what their consumers desire. Nonetheless, when the customer has lost confidence, the poor performance of the service is bound to become even higher, resulting in a drop in customer loyalty and reputation of the company.

Businesses may invest initially to develop the service standards and best practices, but work towards gaining customer trust over a long period. Employees are more likely to maintain high service standards and deliver exceptional services in an environment where small to medium enterprises (SMEs) focus on trust, thereby building and retaining customer trust. One of the reasons that serves as a variable leading to better customer service performance is the increasingly powerful ability of companies to meet their customers' demands and adapt to market changes. It, therefore, means that while the performance of the Customer Trust service for Small and Medium Enterprises (SMEs) is able to build trust indicators, it depends on how well their customer trust service performance indicators perform overall. Therefore, one could hypothesise the following:

H3: Customer Trust has a significant effect on SMEs' service performance.

2.4 The Mediating Effect of Data Analytics Use

The theory which proposes the dependence of the relationship between data analytics use and project success is an interesting field that could be further explored in current business dynamics. The SMEs are realising this opportunity and have started understanding the value of using data analytics for decision-making and improvement in their project management. As new SMEs, resources and money can only be used so much before the business spends every penny on a project to ensure it gets done right.

Intuitively testing this hypothesis should involve breaking it down into a few key components. SMEs are deploying data analytics to unlock the hidden value of their customer information, financial data and operational insights. Moreover, in SMEs, the Performance is evaluated through measures of on-time delivery, compliance with budgeted costs, meeting quality standards and satisfying customer requirements.

There is some hope that these measures may be influenced in a good way by data analytics through several channels. Secondly, it can facilitate the process of data-driven decision-making, which would help SMEs to take scientifically calibrated decisions whilst executing the project. With its ability to process historical data from older projects and external factors, it helps to identify the risks much before they surface. Further, it helps in resource allocation, makes sure the resources are well-utilised & efficiently utilised:

H4: Data analytics use has a significant effect on SMEs' service performance.

The key point of this research is that this study investigates how Technological factors (Perceived Usefulness, Perceived Ease of Use, and Facilitating Conditions), Organizational Factors (Top Management Support, Organizational Culture, and Technology readiness) and Environmental Factors (Competitive Pressure, Social Influence, and Customer Trust) indirectly effect on Small and Medium-sized Enterprises (SMEs) Performance through the mediating effect of data analytics usage.

Data analytics, specifically in this study as the mediator (enabler): It acts as the step between that relates a type of independent variable to its ultimate SMEs service performance outcome. This implies that Data Analytics Use is a critical factor that explains how the independent variables affect Performance within SMEs. In case Data Analytics Use turns out to be a considerable mediator, it means that the independent variables do not affect the performance of SMEs directly, but indirectly through their effect on the adoption and utilisation of data analytics tools.

The mediating effect of Data Analytics Use analysis gives a better insight on the overall effect of the technological, organisational, and environmental factors as a whole on the Performance. It recognises that data analytics serves as the conduit through which these IVs have their effects. Therefore, one could hypothesise the following:

H4a: Data analytics mediates the relationship between Competitive Pressure and SMEs' service performance.

H4b: Data analytics mediates the relationship between Social Influence and SMEs' service performance.

H4c: Data analytics mediates the relationship between Customer Trust and SMEs' service performance.

The research framework of the current study is illustrated in Figure 1 (Appendix).

3 Research Methods

This study employed a quantitative research design. The target population included employees from 12 well-known IT SMEs operating in Jordan, totalling 1802 individuals, drawn from credible sources and official directories such as [12], [13], [14], [15], [16], [17] and [18]. Given the practical limitations of surveying entire populations, a stratified random sampling technique was used to ensure proportional representation across all companies. Using [19] formula, a sample size of 320 was determined to be statistically sufficient, with a 10% buffer added, resulting in 352 distributed surveys to account for possible incomplete or invalid responses. Data collected from the 352 valid responses were analysed using SPSS 30 for descriptive statistics and preliminary analysis, and Smart PLS 4 for structural equation modelling to evaluate the hypothesised relationships and mediating effects. All statistical analyses were conducted using IBM SPSS Statistics 30 and SmartPLS 4. The PLS-SEM was run through the path-weighting scheme and 5,000 bootstrap subsamples, no sign changes option, and one-tailed test significance at 0.05. The questionnaire was formulated as presented in Table 1 which was based on adapting the measurement items in the well-known studies into the context of IT SMEs in Jordan. The items of each construct were critically reviewed and adjusted a bit to make them not only clear and relevant but also consistent with the study goals.

Table 1. Questionnaire Development.

Variable	No. of items	Reference
Competitive Pressure	5	[20]
Social Influence	5	[21], [22]
Customer Trust	5	[23]
Intention to use Data Analytics	5	[24], [25]
SMEs Service Performance	5	[26]

Source: Created by the author

4 Results

The suggested model has been evaluated in the present research in two stages: the measurement model (outer model) and the structural model (inner model) assessments. But before doing these two things, a brief overview of the respondents' profiles is provided:

4.1 Respondent Profile

The first section of the instrument compiled information on the background profiles of the respondents. This information included the respondents' gender, age, and years of experience, among other things. Table 2 located below provides a description of the characteristics that both demographic profiles have in common.

Most of the respondents were males (74.4) and female participants constituted 25.6 percent of the sample. Majorities of the respondents were in the 26-40 years category, representing more than 70 percent of the sample and the largest proportion of

26-30 years (26.1%). Regarding the work experience, most (71.6) participants had a work experience of 1-5 years with 20.2 years following the first group; thus most of the participants were new to their careers. The fact that the number of respondents who have more than 10 years of experience is low indicates that the sample consists of the younger or mid-career IT SMEs professionals as shown in Table 2.

Table 2. Respondent Profile

Items	Answer	Frequency	Percentage
Gender	Male	262	74.40
	Female	90	25.60
Age group	20 – 25 years	16	4.50
	26 – 30 years	92	26.10
	31 – 35 years	79	22.40
	36 – 40 years	81	23
	41 years and above	84	23.90
Years of experience	1 – 5 years	252	71.60
	6 – 10 years	71	20.20
	11 – 15 years	16	4.50
	16 – 20 years	12	3.40
	21 years and above	1	0.30

Source: Created by the author

4.2 Measurement Model

In the initial run, Customer Trust (CT) had a low level of Cronbachs Alpha, Composite Reliability, and Average Variance Extracted of 0.623, 0.671, and 0.482 respectively, which fell short of the recommended 0.70 cutoff of reliability and 0.50 cutoff of AVE [27]. Moreover, there were two items (CT3 and CT4), which had less than acceptable factor loadings of 0.40. Thus, in the second run, a change was introduced and the CT3 and CT4 were eliminated to enhance the scale. The other CT items (CT1 = 0.882, CT2 = 0.922, CT5 = 0.871) had strong loadings and Customer Trust construct had satisfactory reliability (Cronbach's Alpha = 0.871, Composite Reliability = 0.921) and convergent validity (AVE = 0.795). After this adjustment, all constructs had been in line with the suggested measurement criteria (Table 3 and Figure 2 in Appendix).

Second, the Discriminant validity was examined in order to assess how truly distinct a construct is from other constructs. In the field of distinguishing validity, the correlations between variables in the estimation of the model did not exceed .95, as suggested by [28]. The validity was tested based on measurements of the correlations between constructs and the square root of the average variance extracted for a construct, [28], [29]. Table 4 illustrates the results of the Fornell and Larcker Criterion and shows no value above the recommended cutoff point of .95, [28].

Table 3. Convergent Validity

Item	Outer loadings	Cronbach's alpha	Composite reliability	AVE
CP1	0.734	0.859	0.899	0.641
CP2	0.798			
CP3	0.824			
CP4	0.807			
CP5	0.836			
CT1	0.882	0.871	0.921	0.795
CT2	0.922			
CT5	0.871			
DA1	0.810	0.851	0.894	0.630
DA2	0.772			
DA3	0.868			
DA4	0.816			
DA5	0.692			
SI1	0.615	0.814	0.871	0.580
SI2	0.852			
SI3	0.872			
SI4	0.635			
SI5	0.794			
SP1	0.856	0.886	0.916	0.687
SP2	0.842			
SP3	0.826			
SP4	0.830			
SP5	0.788			
CT2 and CT3 were dropped due to low factor loadings, low Cronbach's Alpha, low Composite Reliability, and Low AVE				

Source: Created by the author

Table 4. Discriminant validity - Fornell and Larcker Criterion

	CP	CT	DA	SI	SP
CP	0.800				
CT	0.660	0.892			
DA	0.721	0.645	0.794		
SI	0.211	0.101	0.218	0.761	
SP	0.766	0.617	0.806	0.187	0.828

Source: Created by the author

Moreover, Hetero-trait/Mono-trait ratio (HTMT) is an estimate of what the true correlation between two constructs would be if they were perfectly measured (i.e., if they were perfectly reliable). HTMT is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the Hetero-trait/Mono-trait correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (i.e., the Hetero-trait/Mono-trait correlations) and can be used for discriminant validity assessment [27], [30]. The accepted level of HTMT is .90 (Table 5).

Table 5. Discriminant validity - HTMT

	CD	MC	OP	PP	RC	TMSP
CD						
MC	0.656					
OP	0.619	0.824				
PP	0.105	0.094	0.135			
RC	0.786	0.692	0.670	0.082		
TMSP	0.783	0.800	0.810	0.172	0.793	

Source: Created by the author

4.3 Structural Model

The structural model represents the theoretical or conceptual element of the path model. The structural model (also called the inner model in PLS-SEM) includes the latent variables and their path relationships, [27]. After the measurement model was evaluated, the next step is to assess the structural model. In sync with PLS-SEM, there are five steps involved to assess the structural model, [27]. The steps involved in structural model assessment are (Step 1) assessment of collinearity; (Step 2) assessment of the path coefficients; (Step 3) Coefficient of determination (R^2 value); (Step 4) Effect size f^2; and (Step 5) Assessment of the Mediating Effect.

Table 6 (Appendix) explores the results of PLS bootstrapping, which includes: Beta value, t-values, p-values, hypothesis results (whether supported or not), Confidence Interval for upper and lower levels, f^2, and VIF scores. Furthermore, Figure 3 (Appendix) summarizes the results of the structural model and PLS bootstrapping.

4.3.1 Assessment of the Structural Model for Collinearity Issues

The first step in the structural model is assessing collinearity issues. It is vital to safeguard against collinearity issues between the constructs before performing a latent variable analysis in the structural model. The collinearity is measured by the VIF value. The threshold value for the assessment is 3.3, following, [31]. In this study, as seen in Table 6 (Appendix), all the inner VIF values for the constructs are within 1.025 to 2.400, which are less than 3.3, thus indicating collinearity is not a concern in this study.

4.3.2 Assessing the Significance of the Structural Model Relationships

To test the hypotheses, a bootstrapping procedure is employed to produce results for each path relationship in the model, as shown in Table 6 (Appendix).

Bootstrapping in PLS is a nonparametric test which comprises repeated random sampling with replacement from the original sample to produce a bootstrap sample and to attain standard errors for hypothesis testing, [27]. Regarding the number of resampling, [32] suggested performing bootstrapping with 5000 samples. For this study, five hypotheses are developed for the constructs. To test the significance level, t-statistics for all paths are generated using SmartPLS 4 bootstrapping function. The bootstrapping is set to a 0.05 significance level, a one-tailed test, and 5,000 subsamples. The critical values for a significance level of 5 per cent (α =0.05) are 1.645, respectively, for the one-tailed test, [33].

Furthermore, [27] explain that path coefficients estimated near +1 indicate a strong positive relationship, and the nearer the value is to 0, the weaker the relationships. The following was done with the t-test; relationships whose t-values were greater than 1.645 were taken to be significant at 0.05 level. The analysis has shown that H1 (H2 and H4) relationship of beta = 0.376, t = 7.136, p = 0.001), 0.055, t = 1.862, p = 0.031 and 0.495, t = 9.683, p = 0.001 are significant at the direct level. On the contrary, H3 (0.049, 1.194, 0.116) turned out to be not significant and was, therefore, rejected. Table 6 (Appendix) gives a summary of the results.

4.3.3 The Coefficient of Determination (R^2)

The second task will be to check the predictive power of the model by the value of the coefficient of determination (R^2). This is because the R^2 calculates the predictive power of the model, and it has a range of values between 0 and 1 where a higher R^2 value implies that the model has a high predictive power, [27]. The R^2 is measured with the help of the SmartPLS algorithm as it is presented in Table 6 (Appendix). As there is a variety of rules on the acceptable R^2, this study follows the guideline by [34], giving values of 0.02, 0.13, and 0.26 representing weak, moderate, and substantial levels of predictive accuracy [34]. Overall, referring to Table 7, Competitive Pressure (CP), Social Influence (SI), and Customer Trust (CT) explain 71.3% of the variance in Data Analytics (DA), which indicates a substantial level of predictive accuracy. Moreover, Competitive Pressure (CP), Social Influence (SI), Customer Trust (CT), and Data Analytics (DA) together explain 74.5% of the variance in Service Performance (SP), also indicating a substantial level of predictive accuracy.

Table 7. The coefficient of determination (R^2)

Variable	R-square	R-square adjusted
DA	0.713	0.708
SP	0.745	0.740

Source: Created by the author

4.3.4 Assessment of the effect size (f^2)

In this stage, the effect sizes (f^2) are evaluated. The f^2 computes the relative impact of a predictor construct on endogenous constructs. According to [35], besides reporting the p-value, both the substantive significance (effect size) and statistical significance (p-value) are crucial to be reported. A guideline by [36] is adhered to in order to measure the effect size. According to [36], 0.02, 0.15 and 0.35 are the small, medium and large effects respectively. Based on Table 6 (Appendix), Data Analytics (DA) exerts a high impact on generating the R^2 of Service Performance (SP), whereas Social Influence (SI) exerts a small impact on generating the R^2 of Service Performance (SP).

4.3.5 Assessment of the Mediating Effect

The mediating role of Data Analytics (DA), as shown in Table 8, in the relationship between the independent variables and IT SMEs' Service Performance (SP) was examined through indirect effects using bootstrapping. The findings revealed that there are significant roles played by DA that mediate the effects of Competitive Pressure (CP), Social Influence (SI), and Customer Trust (CT) on SP. In particular, CP → DA → SP ($\beta = 0.253$, $p < 0.001$), SI → DA → SP ($\beta = 0.042$, $p = 0.032$), and CT → DA → SP (0.153, $p = 0.001$) had a statistical significance.

The type of mediation classification indicated that both CP and SI had both significant direct and indirect effects on SP, which means partial mediation. Conversely, CT was significantly indirectly, but not directly, ($p < 0.001$) correlated with SP, which implies complete mediation. The results herein underscore the critical role of DA in converting the market and trust-based drivers into better service performance outcomes by IT SMEs.

Table 8. Mediating Type of Data Analytics.

H	Relationship	Direct Effect on SP (p-value)	Indirect Effect via DA (p-value)	Mediation Type
H4a	CP -> DA -> SP	0.376 (0.000)	0.253 (0.000)	Partial Mediation
H4b	SI -> DA -> SP	0.055 (0.031)	0.042 (0.032)	Partial Mediation
H4c	CT -> DA -> SP	0.049 (0.116)	0.153 (0.000)	Full Mediation

Source: Created by the author

5 Discussion

This study set out to investigate how Competitive Pressure, Social Influence, and Customer Trust affect Service Performance in IT SMEs, and to assess whether those effects are transmitted through Data Analytics use. The results provide a clear picture of which external drivers translate into performance directly, which operate mainly through analytics, and the relative magnitude of those effects, offering a coherent story about how market and relational forces interact with data capabilities to shape service outcomes.

Service Performance is positively and strongly related to Competitive Pressure. This observation implies that the intensity of competition encourages IT SMEs to enhance the results of service provision directly, such as by speeding up the process improvement, elevating the service quality, or refocusing resources on the frontline operations regardless of analytics. Competitive Pressure has a large f^2 and the t-value high value indicates that the relationship is strong.

There is a statistically significant but small impact of social influence on Service Performance. This implies that social norms by peers, customers or industry relations are likely to push SMEs to more desirable practices that will increase service performance marginally, yet social pressure cannot be a significant determinant of performance independently.

Customer Trust had no strong direct impact on Service Performance, which implies that it has no direct contribution to the explained performance. The implication of this finding is that trust itself does not necessarily lead to quantifiable service advancement within the IT SMEs, possibly since trust needs to be operationalized (say, through the means of improved customer data sharing, feedback loops, or joint problem-solving) in order to be able to impact tangible performance indicators.

Data Analytics has a strong, positive direct effect on Service Performance. The use of data analytics substantially enhances service outcomes in IT SMEs, explaining a large share of improvement in responsiveness, reliability, and service quality. The magnitude and significance of this path reinforce the theoretical expectation that capabilities to extract and act on data are a primary mechanism for service improvement.

Turning to mediation, Competitive Pressure continues to exert influence on Service Performance indirectly through Data Analytics. Since the direct effect is still relevant and relevant, the relationship is one of partial mediation: the competitive forces promote the adoption of analytics (which enhances the performance) and results in the promotion of the performance in other ways (e.g., accelerated changes in the processes, price or service repositioning). Equally, Social Influence is partially mediated; social influences have a modest impact on analytics usage that yields service benefits, and a minimal direct impact. These incomplete patterns of mediation imply that analytics plays a significant but not the only role in influencing the results of market and social forces.

Customer Trust has another trend: its indirect impact through Data analytics is considerable and its direct impact on Service performance is not, which means full mediation. This, in practice, implies that trust alone does not lead to improvements in service performance unless it is enabled or incited to use analytics; so, trusted customers might be more disposed to provide detailed usage data or feedback which the firm can analyse to make improvements. The entire mediation outcome highlights the fact that relational assets such as trust must have an operating system (in this case, analytics) in order to be translated into quantifiable performance benefits.

6 Conclusion

This paper has explored how competitive pressure, social influence and customer trust affect the service performance of IT SMEs in Jordan where data analytics has been used as a mediating variable. The results show that competitive pressure and social influence both have direct and indirect impacts on service performance, whereas customer trust is only a mediator in this aspect, which promotes the completeness of data analytics in this association. Furthermore, data analytics, in its turn, proved to be a very powerful indicator of more optimal service performance, which speaks to its central role in converting the external pressure and the relationship dynamics into the actual performance benefits. The fact that these findings confirm the designed framework via the PLS-SEM approach, as well as indicate the potential practical consequences, is that SMEs must focus on the adoption of data analytics to enhance the level of competitiveness, customer loyalty, and social influence to achieve sustainable service quality.

There are various limitations of this study. First, cross-sectional design is a limitation to making causal conclusions with regard to time. Future studies may implement longitudinal methods to study the dynamics of performance changes. Second, the study of IT SMEs in a national setting can be compromised in terms of generalizability. External validity would be enhanced when replicated in other industries and across nations. Third, there is the possibility of bias due to the use of self-reported data. Future studies could incorporate objective performance indicators or multi-source data to enhance robustness. Finally, future research may explore additional contextual factors and alternative modeling approaches to better understand how digital capabilities influence sustained performance.

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APPENDIX

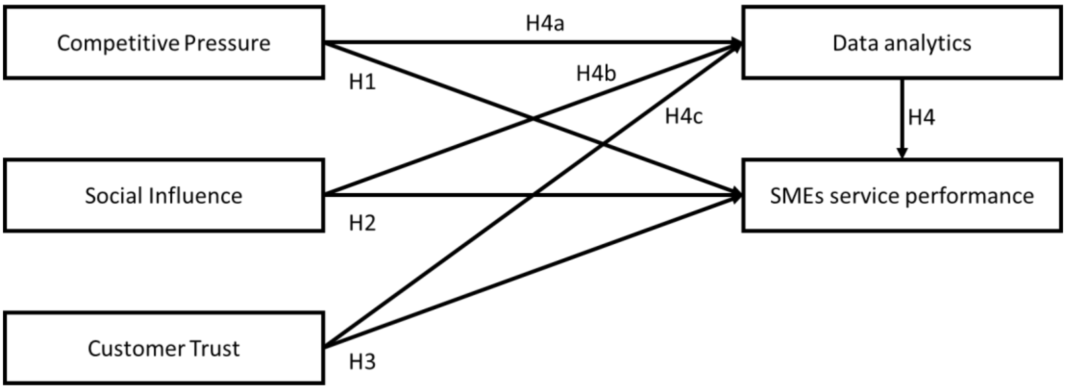

Fig. 1: Research Framework
Source: Created by the author

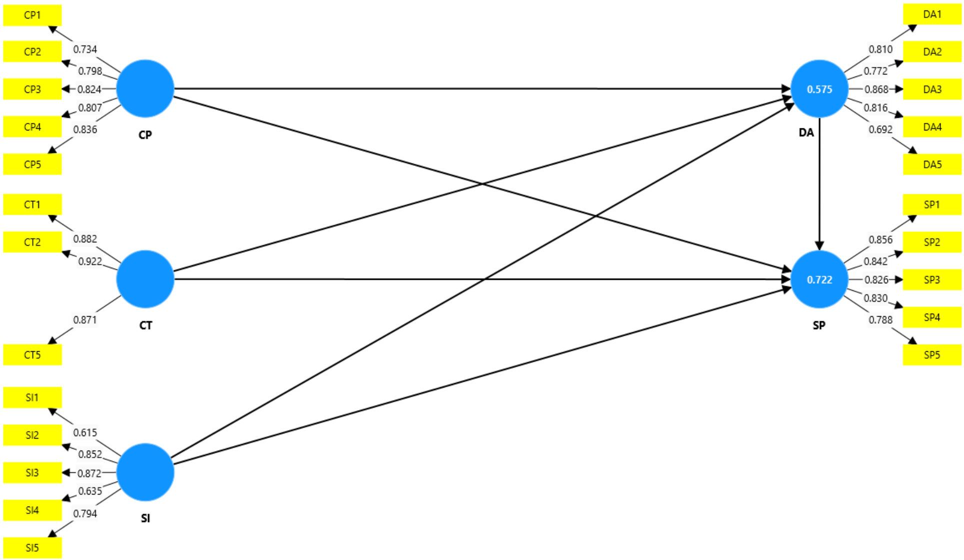

Fig. 2: PLS Algorithm Results
Source: Created by the author

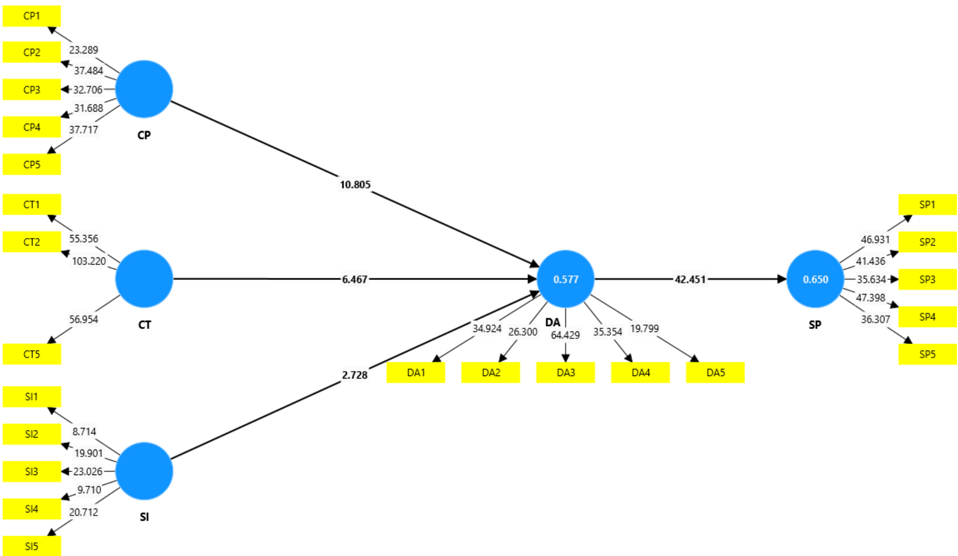

Fig. 3: PLS Bootstrapping Results
Source: Created by the author

Table 6. PLS Bootstrapping Results.

H	Path	Beta	STD Error	T-value	P-values	Decision	Confidence Interval		f^2	Effect Size	VIF	R^2
							5.00%	95.00%				
H1	CP -> SP	0.376	0.053	7.136	0.000	Supported	0.289	0.461	0.384	Large	2.400	0.725
H2	SI -> SP	0.055	0.029	1.862	0.031	Supported	0.005	0.099	0.111	Weak	1.025	
H3	CT -> SP	0.049	0.041	1.194	0.116	Rejected	-0.019	0.118	0.004	No effect	2.006	
H4	DA -> SP	0.495	0.051	9.683	0.000	Supported	0.408	0.577	0.418	Large	2.356	
H4a	CP -> DA -> SP	0.253	0.034	7.508	0.000	Supported	0.198	0.309				
H4b	SI -> DA -> SP	0.042	0.023	1.847	0.032	Supported	0.008	0.076				
H4c	CT -> DA -> SP	0.153	0.028	5.475	0.000	Supported	0.106	0.198				

Source: Created by the author

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.