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Exploring the Drivers of Digital Transformation and their Impacts on Adoption

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ABSTRACT

Digital transformation in industries is essential for industries in order to remain competitive in global world and to achieve sustainable performance. Hence, in order to pursue the driving forces for digital transformation in Pakistan, the present study is being conducted in Textile sector of Pakistan. The drivers of digital transformation are classified in economic, environmental, social, and organizational dimensions. The study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) and a sample size of 124 industrial stakeholders was obtained, and hence the research provides a comprehensive analysis of the influence these drivers have on the adoption o digital technologies in industries. The findings revealed that economic, environmental, and organizational drivers significantly impact digital transformation in the textile sector, and hence it highlights the critical role of financial resources, sustainability initiatives and organizational capabilities within the industry. However, social drivers did not show a significant impact on digital adoption. Additionally, it was concluded that large firms are better at leveraging resources for digital transformation compared to smaller ones. Therefore, conclusion from the study contribute to an understanding of the digital transformation process in developing countries and it offers a practical implications for industry stakeholders and policymakers who are aiming to pave the way for technological advancements within the textile industry of Pakistan.

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1. Introduction

In today's world, digital transformation is essential for the growth of any organization, efficiency and competitiveness (Horvat, Kroll, & Jäger, 2019). It is revolutionizing industries worldwide, thus enabling companies to manage their operations, enhance their decision-making, and interact with customers in innovative ways. Digital technologies help to reshape traditional business models in various ways i.e. from advanced manufacturing systems to data analytics and e-commerce platforms and hence it develops new opportunities for expansion and improvement (Pascucci, Savelli, & Gistri, 2023). Digital transformation paves the way for industrial growth in many ways, First of all, It improves operational efficiency through automation and data analytics. It also facilitates better decision-making and resource allocation. Digital transformation helps to derive personalized services and interactions with customer, and hence customer experiences are enhanced. Moreover, digital transformation drives innovation by fostering flexible business models. It also optimize resource use and increases transparency in system, thus supporting sustainable efforts in industries (Yaqub & Alsabban, 2023). Due to its utmost potential in driving industrial growth, it is essential to understand the drivers and impact of these drivers that stimulate the adoption of digital technologies in order to stay competitive and maintain their agility in an increasingly digital world (Bhatti, Malik, Kamal, Aamir, Alaali, & Ullah, 2021). So keeping in line with above mentioned factors the present study is carried out in the textile sector of Pakistan which is a cornerstone of the country's economy. It has a vast contribution in the GDP, employment, and exports. Despite its economic importance, this sector faces numerous challenges in Pakistan which includes global competition, changing consumer demands and technological advancements. Therefore, adoption of digital technologies seems to be a strategic solution for sustainable growth and improving operational capabilities. However the extent of digital adoption in the textile industry of Pakistan varies due to several factors that includes organizational readiness, workforce skills, financial resources, and external pressures such as market competition and regulatory frameworks (Memon, Aziz, & Qayyum, 2020) the present research aims to identify the key drivers of digital adoption within Pakistan's textile sector and their impacts on the adoption process. Existing studies have primarily focused on developed countries and high-tech industries and thus there remain a significant research gap in this field particularly in context of Pakistan. Hence, it is essential to determine the driving forces for digital transformation and their impact on adoption. The outcomes of the study will provide insights into how textile firms can better leverage digital technologies to improve their competitiveness and resilience in a rapidly evolving market. The findings will also provide implications for policymakers and industry stakeholders thus highlighting areas where support and investment can facilitate more widespread and effective digital adoption.

2. Theoretical framework and hypothesis development

Digital transformation is transforming the industrial landscape. Some studies that highlight the drivers for digital transformation are given below.

Pawar and Dhumal (2024) stated that Digital transformation (DT) significantly boosts employee engagement and empowerment, fosters a culture of collaboration, and helps maintain competitive advantage, all of which are crucial organizational drivers. By integrating digital tools and platforms, employees gain access to real-time information, enabling them to make informed decisions and contribute more effectively to organizational goals. Dodoo et al. (2024) conducted a study which showed how digital transformation enhances workplace safety through the integration of advanced technologies in hazardous industries. By reviewing 48 studies using the PRISMA protocol, the research identified several categories of digital safety systems, including wearables, augmented/virtual reality, AI, and navigation-based systems. These technologies facilitate real-time monitoring, Detection to any possible hazard, and enhanced decision-making capabilities, thereby mitigating risks and promoting safer work environments. Rachkovsky (2024) studied the driving forces for digital transformation. The study indicated that AI, big data, IoT, and organizational adaptation drive digital transformation in organization and it has profound impact on business and economic growth. These have led to the establishment of new setups and these helps to understand market trends and customer behaviours. It streamlines operations and reduces cost. Valenzuela-Ramírez et al. (2024) studied the impact of digital transformation on society. Their study revealed that these technologies have altered how individuals communicate with each other in society. Digital technologies helped in education and training of people. They also paved the way for new business model. Their study highlighted that there are still many people in society who are deprived of these technologies, and thus increasing digital divide and they suggested that there is a need to fill this gape. Bocean and Vărzaru (2023) studied the impact of digital transformation on the economy and sustainability in European countries. Their findings revealed that digital transformation has profound impact on sustainability and economic performance. Computer usage, the Internet in enterprises, and e-commerce with new digital technologies are the noticeable drivers in economic performance. These help in improving efficiency and driving sustainable growth.

Petrescu (2023) studied the interaction of digital transformation with the business world i.e., product development, human resources management, and business models. Results revealed three main drivers of digital transformation which are improving communication, reducing costs, and increasing efficiency. Digital transformation increases efficiency by integrating technologies such as AI, machine learning, and IoT, which enhance data analysis, predictive maintenance, and process optimization. Efficient data management and analysis enable businesses to make informed decisions quickly, streamline operations, and enhance overall productivity. Zhou et al. 2023 studied benefits derived from enterprise digitalization.

The study was conducted in China and results revealed that digital transformation helps companies improve their environmental performance. This effect is stronger in state-owned, large, capital-intensive, and highly polluting companies, as well as those with high financial constraints and those in less competitive markets. The environmental benefits come from technological advances, better management, more skilled workers, and lower financing costs. The study provides new evidence on the sustainability benefits of digital transformation. Truong (2022) studied the digital transformations and its impact on environmental sustainability. A key driver explored in digital transformation is waste management and handling, where digital technologies like IoT, AI, and big data analytics are pivotal. These innovations enable real-time monitoring and optimization of waste processes, enhancing efficiency in collection, sorting, and disposal. Another critical driver is pollution prevention and control, where digital tools play a pivotal role. Technologies such as IoT devices and remote sensing provide real-time environmental data, facilitating prompt responses to pollution events. AI-driven algorithms predict pollution trends and identify sources, enabling targeted interventions to mitigate environmental impact. Danielsen (2021) studied the drivers, opportunities and challenges of digital transformation. Three significant drivers were highlighted in this study namely, the most prominent is turbulent environment which means that it enables the organizations to better adapt to the changing and unpredictable conditions. Second most important driver is reducing operational cost, it enables the organization to be cost efficient. Thirdly, it helps in effective communication within the organization. Hence, it increases the organizations ability to become cost effective and flexible. Díaz et al. (2022) studied the process of digital transformation and its impact on organization. The results revealed that primary goal of digital transformation are to enhance customer experience. Organizations utilize data and create personalized experiences. However, there is numerous privacy issues associated with its implementation, which is needed to be considered. Feroz et al. (2021) identified areas in which digital transformation can drives environmental sustainability. The four areas are pollution control, waste management, sustainable production, and urban sustainability. These allow real time monitoring and predictive maintenance. The study allows avenues for future research on environmental sustainability.

Aly (2020) conducted a study to find the impacts of digital transformation on economic indicators. He finds a positive relationship between digital transformation and economic indicators like economic development, employment and labour productivity. The study noted that females appear to benefit more from digital transformation than males, especially in terms of economic development. Kane et al. (2015) found that these technologies lead to enhanced communication and collaboration hence they facilitate seamless interaction among team members. By breaking down silos, these technologies promote a collaborative work environment where information flows freely and team members can easily share ideas, feedback, and updates in real time. This fosters greater teamwork, enhances decision-making processes, and improves overall productivity. Sabbagh et al. (2013) studied the digitalization as pivotal economic driver as it increased output and created more jobs in a sluggish economy during the year 2011. It highlights how digitization impacts developed and developing economies differently i.e., boosting productivity and growth in developed nations while potentially leading to job losses due to outsourcing, whereas emerging markets benefit more in job creation through export-driven sectors. The study advocated for digitalization plans, capability development, and collaborative ICT ecosystems to maximize economic gains and having an inclusive growth across diverse global contexts. Based on the following literature, we can group drivers into four categories i.e. economic, social, environmental and organizational.

Table 1

Variables	Description	References
Economic Drivers	It saves cost by elimination of manual work. It helps to gain customer satisfaction and loyalty. It helps to achieve efficiency. It enhances decision making through advanced data analytics.	Rachkovsky (2024) Zhou, Jiang, and Zhang (2023) PETRESCU et al. (2023) Danielsen (2021)
Environmental Drivers	It helps to achieve sustainable industrial practices. It paves the way to adopt green technologies like energy efficient devices. It helps to reduce harmful emissions.	Feroz, Zo, and Chiravuri (2021) Truong (2022) Bocean and Vărzaru (2023) Zhou, Jiang, and Zhang (2023)

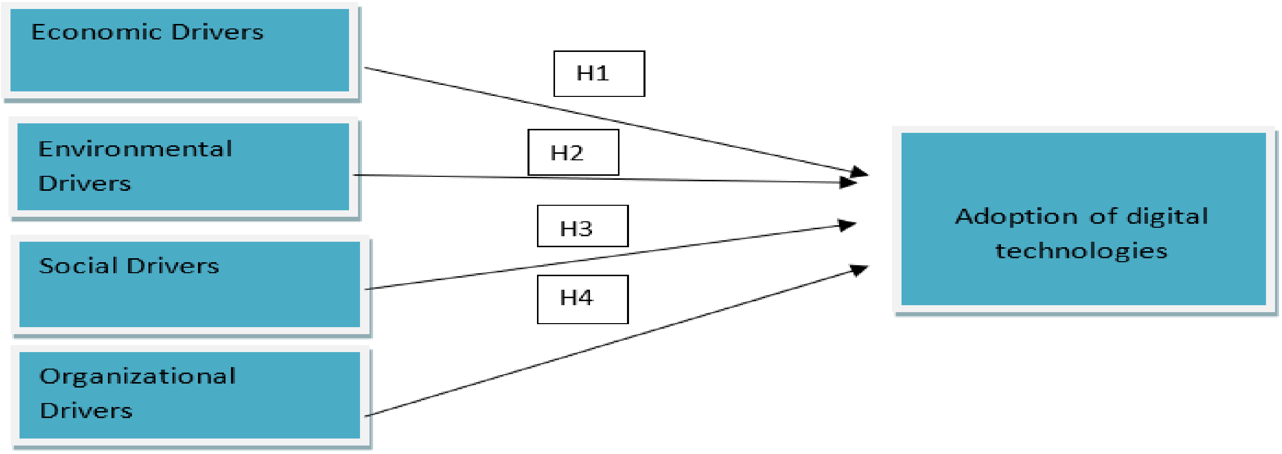
Social Drivers	It promotes circular economy practices. It helps to improve work place conditions. It helps to create more jobs. It increases the productivity of workers. It removes social inequality.	Sabbagh et al. (2013) Dodoo, Al-Samarraie, Alzahrani, Lonsdale, and Alalwan (2024)
Organizational Drivers	It increases employee engagement and empowerment. It helps organization to remain competitive. It creates a culture of collaboration among employees. It increases the process of transparency.	Aly (2020) Pawar and Dhumal (2024) Kane et al. (2015) Díaz, Guerra, and Díaz (2022) PETRESCU et al. (2023)

On the basis of these, following hypothesis are formed

H_1: Economic drivers significantly impact adoption of digital technologies
H_2: Environmental drivers significantly impact adoption of digital technologies
H_3: Social drivers significantly impact adoption of digital technologies
H_4: Organizational drivers significantly impact adoption of digital technologies.

The framework for the study is represented in the image 1.1

Figure 1: Research framework



3. Methodology

3.1. Research instrument

The study was conducted by using questionnaire as a research instrument.. By referring to the literature constructs were identified and these were incorporated in questionnaire. The responses were collected on a five point Likert scale. Before data collection, pilot testing was performed on the output collected from industrial experts. The questionnaire consisted of 20 items. The likert scale points ranged from 1 to 5 showing strongly disagreed to strongly agreed.

3.2. Sample and sampling technique

A convenience sampling approach was used as a data collection strategy. The target individuals of our study were the directors and management levels. Telephonic and face to face surveys were conducted. Initially, we targeted 150 industries, but managed to collect data from 139 industries. Out of 139 industries, 15 responses were invalid and hence, we started our analysis with 124 usable data.

3.3. Data analysis technique

PLS-SEM modelling was used as data analysis technique it is a powerful statistical technique used for modeling complex relationships between observed and latent variables. Its flexibility and robustness make it ideal for studies with small sample sizes and complex models. Henseler, Ringle, and Sinkovics (2009).

4. Results and Discussion

This section comprises result and discussion of the analysis. The demographic profile of respondents is presented in Table 2. The study has categorized industry into four types i.e. spinning industries, weaving, and dying followed by printing. The experienced is classified into four categories ranging from 0 to 5 years, 5 to 10 years, 10 to 15 years and experience greater than 15 years, Majority of the respondents belonged to the third category i.e., most of the respondents have experience ranging from 10 to 15 years. Most of the participants belonged to top management, followed by middle management and a few belonged to director category. The size of industry is classified into three categories small, medium and large and number of employees was used to indicate the firm size with any industry up to 250 employees was labeled as small, whereas between 250 to 500 employees as medium and more than 500 as large firms. Most of the industries in our data belonged to large category having number of employees greater than 50.

Table 2: Profile of respondents

Participants	N	Industry	N	Experience	N	Size	N
CEO/Director	8	Spinning sector	30	0-5	10	Small	19
Upper Management	59	Weaving sector	19	5-10	34	Medium	36
Middle management	57	Dying sector	40	10-15	45	Large	69
		Printing sector	35	More than 15	35		
Total	124	Total	124	Total	124	Total	124

4.1. Reliability and Validity

For the confirmation of reliability and validity of the data Cronbach's alpha value is used along with composite reliability (rho_a) and composite reliability (rho_c). Conbach's alpha assesses internal consistency by estimating the average correlation among items within a construct. Values above 0.70 are generally considered acceptable. Composite reliability (rho_c) is more commonly used as compared to composite reliability (rho_a) to check the internal consistency of the constructs, values above 0.70 are considered acceptable. An AVE of 0.50 or higher is considered adequate (Hair, Ringle, & Sarstedt, 2011). Referring to the threshold values and comparing it with the results it seems that all the values lie within the acceptable ranges. Hence, we can say that our model is acceptable in terms of reliability and validity.

Table 3: Reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Adoption	0.751	0.76	0.842	0.572
EcoDriver	0.727	0.746	0.828	0.547
EnvDriver	0.765	0.766	0.85	0.587
OrgDriver	0.716	0.725	0.824	0.541
SocialDriver	0.704	0.712	0.817	0.528

4.2. Discriminant validity

Discriminant validity is an important measure for the determination of construct validity. It shows that a construct is unique from other constructs in a model and therefore it shows that the constructs measure different concepts. Two commonly used measures for discriminant validity are the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion. The HTMT ratio compares the average correlations between indicators across different constructs with the average correlations of indicators within the same construct. A HTMT value below 0.90 (or 0.85 in more conservative view) indicates acceptable discriminant validity. The Fornell-Larcker criterion assesses discriminant validity by comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations between that construct and other constructs in the model (Fornell & Larcker, 1981). The square root of the AVE for each construct should be greater than its highest correlation with any other construct (Hock & Ringle, 2010). Following the concepts presented in table 3 and table 4, it is clear that our model has discriminant validity.

Table 4: Heterotrait-Monotrait (HTMT) ratio

	Adoption	Eco Driver	Env Driver	Org Driver	Soc Driver
Adoption					
EcoDriver	0.846				
EnvDriver	0.894	0.693			
OrgDriver	0.87	0.67	0.711		
SocialDriver	0.516	0.442	0.383	0.585	

Table 5: Fornell& Larker Criteria

	Adoption	Eco Driver	Env Driver	Org Driver	Soc Driver
Adoption	0.756				
EcoDriver	0.66	0.739			
EnvDriver	0.683	0.54	0.766		
OrgDriver	0.64	0.506	0.539	0.736	
SocialDriver	0.389	0.332	0.289	0.417	0.726

4.3. Variance Inflation Factor

Variance inflation factor (VIF) is an important measure used to detect multicollinearity in regression models. Multicollinearity occurs when independent variables are highly correlated, potentially causing issues with the stability and interpretability of the regression coefficients. VIF value shows how much the variance of a regression coefficient is inflated due to collinearity with other predictors. A VIF value of 1 indicates no correlation, values between 1 and 5 suggest moderate correlation, and values above 5 (sometimes more conservatively above 10) signal high multicollinearity, warranting further investigation or remedial action (Hair, Ringle, & Sarstedt, 2011). From the Table 6 and Table 7, it is clear that our model does not suffer from collinearity issues.
The results of measurement model are presented in Figure 2.

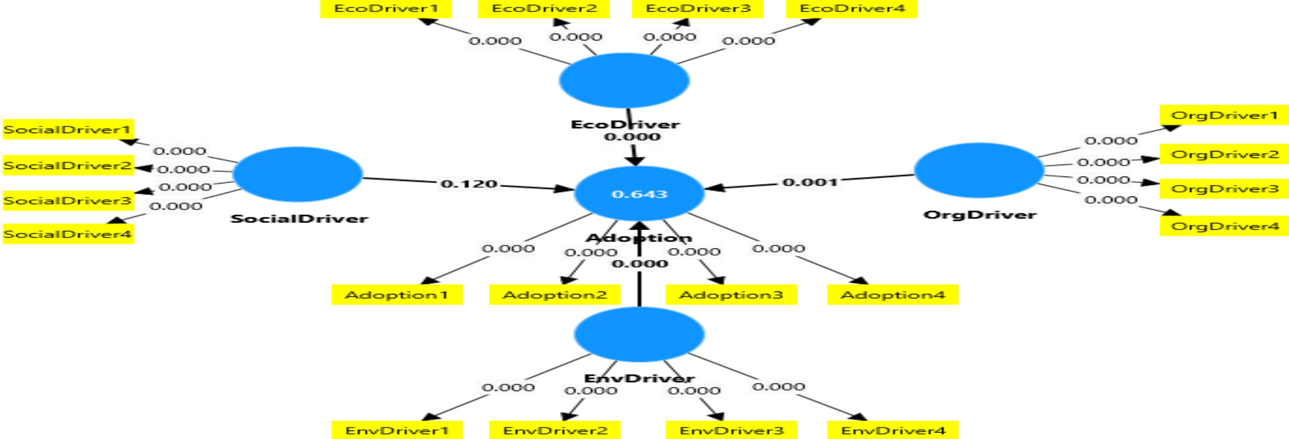
Table 6: VIF (outer model)

Constructs	VIF	Constructs	VIF
Adoption1	1.321	EnvDriver3	1.547
Adoption2	1.574	EnvDriver4	1.413
Adoption3	1.504	OrgDriver1	1.463
Adoption4	1.427	OrgDriver2	1.266
EcoDriver1	1.477	OrgDriver3	1.335
EcoDriver2	1.341	OrgDriver4	1.651
EcoDriver3	1.276	SocialDriver1	1.57
EcoDriver4	1.564	SocialDriver2	1.626
EnvDriver1	1.609	SocialDriver3	1.594
EnvDriver2	1.451	SocialDriver4	1.531

Table 7: VIF (inner model)

Variables	VIF
EcoDriver -> Adoption	1.582
EnvDriver -> Adoption	1.631
OrgDriver -> Adoption	1.681
SocialDriver -> Adoption	1.242

Figure 2: Measurement model



4.4. Model Fitness

Model fit criteria for PLS-SEM is evaluated by the measures like SRMR, d_g andNormized Fit index(NFI) values. NFI evaluates the fit of the model by comparing the proposed model's chi-square value to a null model, with values closer to 1 indicating better fit. Referring to the result, our model has NFI value of 0.64 indicating it as a moderate fit. Standardized Root Mean Square Residual (SRMR) assesses the average magnitude of residuals between observed and predicted correlations, where a value below 0.1 or in a more strict view a value below 0.08 is considered a good fit. Since the calculated values lies below 0.1 and equal to 0.09. Hence, it is considered as acceptable value. Moreover, the computed value of d_g should lie in between the upper and lower bound of confidence interval measure (Hu & Bentler, 1998). The calculated value lies in the limit of CI at 95% have 0.52 values, whereas 99% have 0.592 values. Overall, the model can be considered as good fit model by considering all the values.

Table 8: Model fitness criteria

Measures	Saturated model	Estimated model
SRMR	0.08	0.08
d_G	0.543	0.543
NFI	0.64	0.64

4.5. Predictive accuracy and coefficient of determination

Q^2 evaluates the model's ability to predict out-of-sample data. A Q^2 value greater than zero indicates that the model has predictive relevance, with higher values suggesting better predictive accuracy while, coefficient of determination R^2 measures the explanatory power of the model and UTS value ranges from 0 to 100. Higher values indicate a good explanatory power of the mode (Hair, Ringle, & Sarstedt, 2011). Referring to our results it is clear that the model has a good predictive and explanatory power as represented by the Q^2 and R^2 value. The output is present in Table 9.

Table 9: Goodness of fit and predictive accuracy

	Q^2predict	R-square	R-square adjusted
Adoption	0.597	0.643	0.632

4.6. Hypothesis testing

The result of structural model is shown in the table and represented in the image. From the Table 10 it is evident that economical drivers (β = 0.309, P=0.00), environmental drivers (β=0.344, P=0.00) and organizational drivers (β=0.274, P=0.001) has a positive and significant impact on the adoption of digital transformation as we proposed in our hypothesis. But social drivers don't have significant impact on the adoption of digital transformation and it is found to be in contradiction with our proposed hypothesis. The result of structural model is present in Figure 3.

Figure 3: Structural model

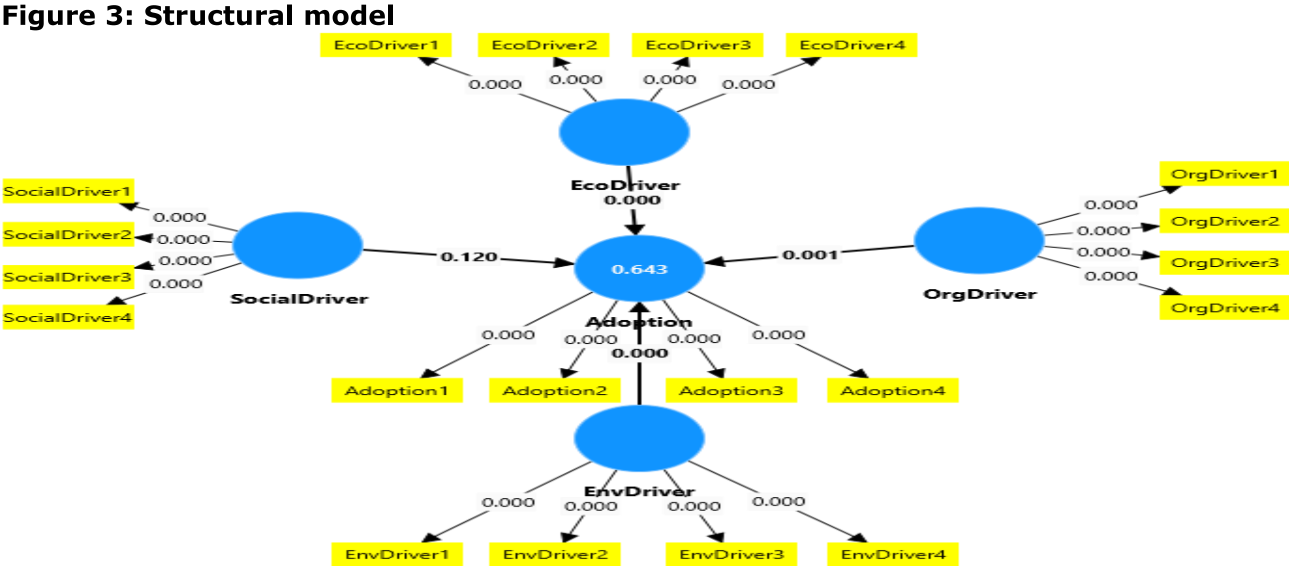


Table 10: Results of hypotheses

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	P value
EcoDriver -> Adoption	0.313	0.309	0.078	0
EnvDriver -> Adoption	0.351	0.344	0.076	0
OrgDriver -> Adoption	0.262	0.274	0.081	0.001
SocialDriver -> Adoption	0.074	0.08	0.063	0.12

The contradiction may occur due to the fact that the study is performed in a developing country like Pakistan. There is skepticism in people regarding its social benefits as people are not fully awarded as if these technologies would provide new jobs or they can reduce income inequalityMoreover, comprehending the social benefits of technology adoption requires time, as their social benefits are not immediately evident (Bantilan & Padmaja, 2008). Industries tend to prioritize gains in terms of economic, environmental and organizational aspects.

5. Conclusions

The present study investigated the influence of economic, environmental, social, and organizational drivers on the adoption of digital technologies within the textile sector of Pakistan. The findings revealed that economic, environmental and organizational factors play significant role in the adoption of digital transformation initiatives within the industry. This highlights the importance of considering economic, environmental, and organizational implications when implementing digital technologies in the textile sector. However, the social driver was found to be insignificant and this it suggests that social factors may have less direct impact on the adoption of digital technologies. These results provide valuable insights for policymakers, industry stakeholders, and organizational stakeholders who are seeking to promote and facilitate the digital transformation of the textile sector in Pakistan and it also enlightens the importance of formulation of policies that promote economic, environmental and organizational aspects.

5.1. Study limitation and Future research implications

The study has various limitations. First of all, the current study was focused only on one sector. Secondly, the study was cross sectional in nature limiting the understanding of factors across time frame. Furthermore, the sample size was small that resists its generalization. Keeping in considerations the above limitations, in future studies could be conducted that will include multiple sectors that will increase the diversity and representation of factors that will influence adoption. Longitudinal studies should be conducted so that these factors can be analyzed across time frame.

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