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Knowledge Management as a Mediating Variable in the Relationship Between Digital Transformation and Enterprise Performance

Keywords:
Digital Transformation; Knowledge Management; Enterprise Performance; PLS-SEM Approach.

Abstract

The main objective of this study is to develop a structural causal model that integrates both direct and indirect relationships among the study variables to measure the causal link between digital transformation and enterprise performance, with knowledge management acting as a mediating variable. Data were collected from 72 personnel working in Tramway Management enterprises in Western Algeria (SETRAM), responsible for urban transportation in Oran, Mostaganem, and Sidi Bel Abbes—cities characterised by high population densities. A purposive (judgmental) sampling method was employed, and the collected data were analysed using the PLS-SEM approach.

The research demonstrates a strong, direct positive relationship between digital transformation and knowledge management, as well as between knowledge management and enterprise performance. Although digital transformation also exerts a positive and statistically significant influence on enterprise performance, this effect is not particularly strong. Importantly, knowledge management exhibits a partial mediating role in the link between digital transformation and enterprise performance.

The study offers insights into how government-supervised institutions perform during digital transformation. Findings emphasise the need to invest in digital transformation and knowledge management to maintain institutional continuity in line with Algeria's economic reforms.

This empirical study contributes to the ongoing debate by demonstrating that digital transformation enhances enterprise performance, particularly through the mediating role of knowledge management.

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1. Introduction

Amidst the fierce competition and rapid changes imposed by the Fourth Industrial Revolution. Digital transformation (DT) has evolved into a strategic necessity for organisations aspiring to achieve operational excellence and ensure sustainable market presence (Xue et al., 2024). Far from being confined to the adoption of novel technologies, DT embodies a profound metamorphosis of business models, processes, and the very culture of an organisation (Deep, 2023; Kraus et al., 2022; Nozari, 2024). Recently, considerable studies have extensively examined certain methods to leverage the performance of enterprises focusing on DT (Do et al., 2022; Masoud & Basahel, 2023; Zheng et al., 2023), knowledge management (KM) (Iqbal et al., 2025; Law, 2025; Siregar et al., 2021). Moreover, there is some evidence in the relevant literature that the correlation between DT and Enterprise performance (EP) is neither direct nor simple, but rather it is a more indirect relationship through mediation by other variables, namely KM (Asbeetah et al., 2025; Jiang et al., 2025; Ringle et al., 2023; Sijabat, 2022).

KM has been a key component in driving strategic imperatives in organisations seeking to gain a competitive advantage and drive growth, and further, become a catalyst for DT (Akosen & Asiedu, 2023). KM is regarded as one of the three fundamental components of DT, along with the management of main structures and the management of application programming interfaces. Several scholars contend that the DT approach relies on the amalgamation of KM, an adjustment to the organisational ethos, and the assimilation of digital technologies into the company process (Erceg & Zoranović, 2022).

Over the past decades, DT has been a substantial focus for many researchers and practitioners. DT encompasses the profound changes that are happening in every aspect of society, organizations, and industries through the use of digital technologies such as artificial intelligence (AI), big data analytics the Internet of Things (IOT), blockchain (Truong, 2022), and automation to redefine business processes, develop innovative models, and create added value for both customers and stakeholders (Kelečević & Lesjak, 2025), so that the data barrier between the enterprise and the various levels of the industry can be further opened up, promoting the improvement of the operational efficiency of the overall business, and then establishing a new digital System (Wang & Sun, 2025). Companies see DT as an opportunity to increase their competitive advantage and evolve Business Models in line with new trends (Billi & Bernardo, 2025). Furthermore, the application of digital tools accelerates the conversion of innovation outcomes, enabling companies to quickly launch new products or services to meet market demand, thereby further enhancing their competitiveness (Mu et al., 2025), and help create value and improve performance (Peng & Tao, 2022).

Currently, the digital economy is often regarded as the primary driving force behind the global environment, providing a novel and essential approach for nations to enhance the calibre of their economic progress. Countries like the United States, Germany, France, Canada, India, and other nations have prioritised DT as the central focus in developing their economies. Adopting DT is now essential for both survival and sustained growth (Li et al., 2023). Algeria, like other countries, in its efforts to develop its national economy, has witnessed a significant and tangible shift in the utilisation of information technology and digitalisation in public institutions.

To address urban transportation challenges, the Algerian government has initiated policies to improve mobility through dedicated transport systems like the metro in Algiers and tramways in seven cities, including Algiers, Oran, Mostaganem, and Sidi Bel Abbes, and others. These initiatives aim to balance urban transportation supply and demand, as wells as promoting sustainability (Boudjeriou & Kebiche, 2024). For instance, the Tramway Management enterprises of Western Algeria (SETRAM), responsible for urban transportation in the cities of Oran, Mostaganem, and Sidi Bel Abbes, has made a qualitative leap in DT and

KM. It has also launched an online payment site aimed at providing an exceptional experience for customers before their tramway journeys. This site allows customers to easily purchase or refill their subscriptions through the "electronic payment" service, track their consumption, and submit complaints and suggestions to improve services and meet customer needs. The tramway institutions have also empowered employees with all forms of DT, including modern software and applications, as well as improving research and internal development. In light of the previous discussion, the study aims to answer the following questions:

- RQ1. How does DT affect the EP of SETRAM?
- RQ2. How does DT affect the KM of SETRAM?
- RQ3. How does KM affect the EP of SETRAM?
- RQ4. To what extent does KM mediate the relationship between DT and the EP of SETRAM?

This study contributes to the literature by: (1) addressing a research gap through its examination of KM's mediating role in the DT-EP relationship; (2) tackling the scarcity of large scale research on this topic specifically within Algeria's tramway sector; (3) developing a causal model to clarify the direct and indirect linkages between DT,KM, and EP; and (4) providing valuable, practical insights for decision- makers on leveraging DT and enhancing KM in public and urban transportation.

2. Theoretical background and hypotheses

The theoretical background section reviews existing literature on DT, KM, and EP, examining both the theoretical foundations and empirical findings concerning their relationships. Based on this synthesis, a conceptual model was formulated to test these associations via four explicit hypotheses.

2.1 Digital transformation

The Fourth Industrial Revolution –often termed Industry 4.0− is characterized by the pervasive utilization of digital technology, which is itself propelled by the profelation of digital networks (P. Chen & Kim, 2023). This technological advancement and digitization represent a genuine revolution in the corporate world environment and markets, particularly in the ways organizations operate through the application of innovative computer sciences, such as the IOT , cloud computing, blockchain, big data analytics, AI, machine learning, and others (Gagliardi et al., 2023). As a recent example, the use of Internet of Things technology, enables the extraction and refinement of large amounts of data, a process that was impossible in the past (Nozari, 2024). Similarly, integrating AI/ML into software quality assurance introduces intelligent automation, data-driven decision-making, and enhanced adaptability, ultimately contributing to higher software quality and more efficient testing processes (Owoc & Stambulski, 2025). Blockchain systems are also considered tools that tangibly improve working conditions and fight corruption and labor abuses by reinforcing accountability and transparency (Khan et al., 2025). For instance, the decentralized mining system inherently detects and rejects any fraudulent transaction, preventing it from being recorded on the blocks (Zenagui et al., 2024).

This transformation in how digital technologies and techniques are utilized to build innovative organizational changes is known today as "Digital Transformation". This transformation takes into account a wide range of changes, including organizational culture, operational shifts, and the integration of digital technologies, guidance, and capabilities at all organizational levels (Slavkovic et al., 2023). Consequently, DT refers to a significant process of change that is achieved through the utilization of computer-based AI, aimed at achieving performance improvement and innovation in organizations (Xu et al., 2022).

The primary objective of DT is to resolve obstacles associated with efficiency and effectiveness. Organizations that fail to promptly formulate and execute DT plans are unlikely to remain competitive in the emerging digital landscape (Kraus et al., 2022). DT leads to the generation of substantial and novel quantities of data, which can enhance decision-making and strategic planning (Abd Al-Khaleq & abd Al-Jabbar, 2022). As a result, digital technologies accelerate the pace of change and bring about substantial transformations in various industries (Billi & Bernardo, 2025). Thus, helps companies build competitive advantage, leading to improved performance.

DT is attractive because it enables the integration and expansion of production processes both within and across organizations, but it is also a great challenge. A very small percentage of companies succeed. The success of the DT depends heavily on digital maturity. When we talk about DT, in which the human factor plays an important role (Jakab et al., 2023).

2.2 Knowledge management

The effective utilization of information and skills to address challenges and fulfill the organization's requirements has become indispensable, requiring special management known in the scientific literature as KM (Mazhar & Akhtar, 2018). The discourse on KM can be traced back to the 1950s, when the importance of integrating implicit and explicit knowledge was first emphasized. This foundational idea gained momentum in the following decade. By the early 1960s, the development of KM began to take shape, primarily concerned with codifying knowledge and storing explicit knowledge, reflecting the era's emphasis on learning through best practices and lessons. The conjunction of implicit and explicit knowledge, recognized earlier, continued to fuel the ongoing KM debate. From the 1990s to the early 2000s, this evolution culminated in the conception of knowledge as a critical economic resource in the emerging knowledgesociety (Machado et al., 2022), it contributes to strengthening long-term sustainability and support competitive advantage (Lee, 2018). KM refers to the capacity to effectively handle information by gathering knowledge from both endogenous and exogenous factors and consequently transforming it into new plans or concepts, and executing and sustaining them (Idrees et al., 2023). Many studies agree that knowledge is divided into: Firstly, tacit knowledge: The knowledge an individual possesses but is challenging to formalize or explain and share with others (Siregar et al., 2021). Secondly, explicit knowledge: This refers to knowledge that is clearly expressed through writing, computer programs, or graphics, and may be obtained by educational activities such as cooperation, cultivation, and retention (Anshari et al., 2023).

Referring to the literature and previous research, there is a variation among researchers in classifying and determining the number of KM processes. For example, Ode & Ayavoo (2020) relied on four dimensions of KM: knowledge generation, knowledge storage, knowledge diffusion , knowledge application. According to Al Hbabi and Alomari (2020) KM methods encompass knowledge acquisition, knowledge storage, knowledge sharing, and knowledge application. Torres et al. (2018) indicate that knowledge management processes consist of: knowledge acquisition, knowledge generation, knowledge sharing, and knowledge application (Flores López et al., 2023).

According to Koulopoulos and Frappaolo (2001) , there exist five functions of KM applications within an organization: Mediation, Externalization, Absorption, Perception and Measurement. KM seeks to effectively gather, safeguard, distribute, and recycle both implicit (Ribeiro et al., 2022). It also positively impacts organizational processes and supports methods and approaches to innovation (Ding et al., 2019). Additionally, it enhances productivity by creating, disseminating, and retaining knowledge while delivering higher value to the organization and fostering a culture of knowledge sharing (Torabi & El-Den, 2017).

2.3 **Enterprise** performance

EP is an indication of the organization's condition at a specific timeframe. It can be defined as the outcomes or accomplishments that are influenced by the operational activities of the company in the effective utilization of the available resources. In general, it is a broad concept that encompasses various dimensions of administrative processes and an organization's competitive advantages, comprising both financial and non-financial performance (Hartono et al., 2023). According to Cao and Zhang (2011), performance is a metric that quantifies an organization's capacity to accomplish its objectives and objectives compared to its key competitors (Masoud & Basahel, 2023). There are 3 types of EP: multidimensionality, dynamism, and comparability. Multidimensionality is a difference of opinion because there are many stakeholders, differences in strategy, and differences in size in understanding. Dynamism is the goal of senior managers in managing firm performance to earn superior returns for shareholders both in the long and short term. And the last, comparability is the proper benchmarking in analyzing competitor companies in market share (Novitasari & Agustia, 2021). EP is an important measure of success, and business administration factors play a key role in shaping EP. Organizational structure is the framework within the firm that determines the distribution of authority and responsibility, information flow and decision making hierarchy, and its impact on firm performance includes efficiency and innovation aspects (Wang & Sun, 2025). In other words, it focuses on the unique elements that distinguish the organization from others and can be measured by profits, sales volume, market share, etc (Lorino, 1997).

2.4 Hypotheses and model

Referring to previous studies, Scott et al. (2017) discovered that the adoption of new technology has a direct positive effect (DT) on the financial sector, specifically on EP. Similarly, Guo and Xu (2021) found that EP is significantly influenced by DT (Masoud & Basahel, 2023). The study by Chen et al. (2024) concluded an important finding that DT has a positive impact on all knowledge production processes, which positively reflects on the knowledge aggregation processes in Chinese manufacturing companies. However, there is still debate over how DT affects EP. On the one hand, DT promotes the rationalization of production operations as well as improves asset utilization and innovation; this, in turn, enhances EP (Zheng et al., 2023). The study of Do et al.(2022) shows that the DT has a positive impact on the performance of Vietnamese commercial banks. Besides, we also find that the larger the banks, the greater the positive impact of DT on bank performance. The research results of (Rio Rita & Nastiti, 2024) revealed that financial bootstrapping and DT have a significant positive effect on the financial performance of (MSMEs). Therfore, the findings of Mangifera and Mawardi (2022) establish a positive relationship between DT and financial performance in small and medium-sized enterprises (MSMEs). Based on these arguments, it could be hypothesized that:

H$_1$: DT has significant and positive impact on EP.

In recent years, numerous researchers have contributed literature to provide a fruitful integration of KM and Industry 4.0 during the era of DT (Machado et al., 2022). Where the study of Kartoyo et al. (2023) showed that DT leadership as a significant influence on KM. The implementation of DT in a company influences the different KM operations and needs the adaptation of its KM strategy. In a recent study, it was concluded that DT has a direct and positive impact on green knowledge acquisition (Asbeetah et al., 2025). And DT can also improve the capability of tacit knowledge absorption and, through the learning process can lead to new explicit knowledge (Sánchez Ramírez et al., 2022). Based on these arguments, it could be hypothesized that:

H$_2$: DT has significant and positive impact on KM.

It has been founded that KM including knowledge process and infrastructure capabilities affect positively in a huge manner on all aspects of EP directly or indirectly (Abuaddous et al., 2018) . Moreover, the results of the study (Eid et al., 2021) indicated that the measurements of KM (knowledge acquisition, knowledge storage, knowledge distribution, and knowledge application) have a positive impact on EP. This was also found in recent study (Alhawamdeh et al., 2024) that observed a significant positive impact of KM on EP in service organizations and the tourism sector in Jordan. The research results (Dzenopoljac et al., 2018) revealed that all 4 KM processes examined (i.e., knowledge generation and development, codification and storage, transfer and sharing, and use and evaluation) have a positive and significant impact on perceived business performance. Additionally, the research revealed that KM processes have the highest impact on innovation performance. In another study, (Ştefan et al., 2024) found a positive relationship between the combined dimensions of KM and organizational performance. The study conducted by Iqbal et al.(2025) demonstrate that knowledge sharing significantly fosters EP. Based on these arguments, it could be hypothesized that:

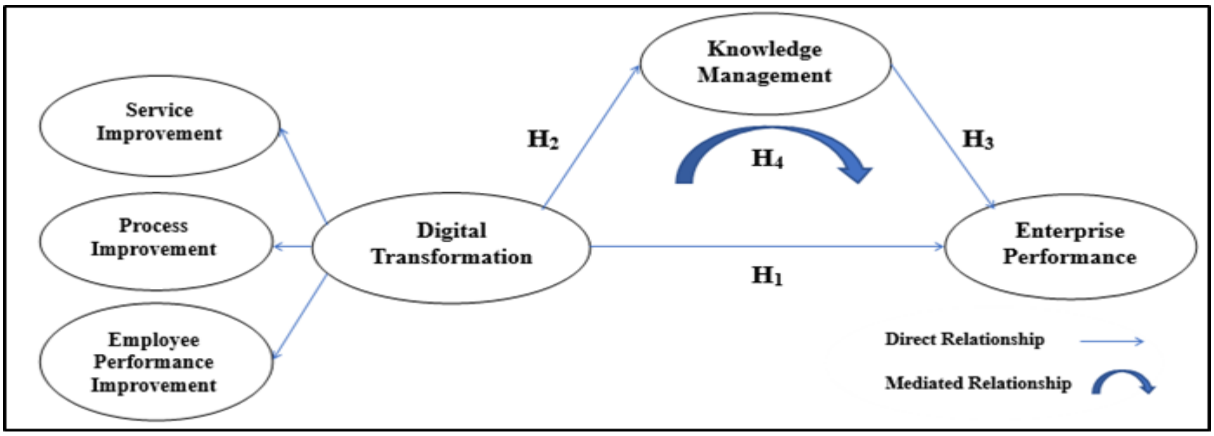
H3: KM has significant and positive impact on EP.

According to Wang & Wang (2012) discovered that both overt and covert knowledge-sharing strategies enhance creativity and performance. The rate of innovation and financial performance are both positively impacted by the sharing of explicit knowledge, while implicit knowledge sharing has a positive impact on the quality of innovation and operational performance. The results of the study by Asbeetah et al.(2025) showed that DT positively impacts sustainable corporate performance, with green knowledge acquisition acting as an important mediator in this relationship. Meanwhile, the study by Sijabat (2022) concluded an important result that DT positively impacts performance, but this relationship is stronger when KM is present as a mediating variable. A study by Kartoyo et al.(2023) found that DT has less impact on performance in the absence of KM. Based on these arguments, it could be hypothesized that:

H4: KM mediates the relationship between DT and EP.

Based on the insights gained from the literature review that support and validate the current study model, along with its hypotheses based on the model proposed by Baron and Kenny (1986), the model is shown in Figure 1.

Figure 1. Study Model



3. Research methods and procedure

The current research is an empirical study conducted in the Algerian enterprises environment. Which involves testing hypotheses based on previous literature and deriving results from general concepts to specific findings. A quantitative method using the PLS-SEM Approach was employed to obtain results and eliminate biases.

3.1 Questionnaire design

To achieve the intended objectives of this study, a questionnaire was prepared and developed based on a literature review, utilizing closed-ended data. It leveraged the renowned Likert 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree) to allow for extensive responses across the three main variables, followed by the respondents' demographic profiles. As showin the following table:

Table 1. Constructs, Dimensions, and Sources of Measurement Scales.

Constructs	Dimensions	Sources of measurement scales	Number of Items
EP	One- dimensional	(Wang & Wang, 2012; Hartono et al., 2023; Metwally et al., 2024; Cristache et al., 2025)	07
DT	Service improvement	(Zhao et al., 2023; Atobishi et al., 2024)	04
	Process improvement	(Al-Ayed et al., 2023; Zhao et al., 2023)	04
	Employee performance improvement	(Yu & Moon, 2021; Al-Ayed et al., 2023)	04
KM	One- dimensional	(Namdarian et al., 2020; Ode & Ayavoo, 2020; Wolor et al., 2023; Cristache et al., 2025)	09

3.2 Sample and data collection

This study adopted a quantitative approach and used the questionnaire as a tool for data collection. The questionnaire was self-distributed and collected by the research team to ensure the purpose of the research was clear for participants and to ensure a high response rate. The entire workforce is included in the research population at the Western Algerian Tramway Lines Management enterprises (SETRAM), Responsible for urban transportation in the cities of Oran, Mostaganem, and Sidi Bel Abbes, which are known for their high population density. The study sample was selected using purposive or judgmental sampling, commonly known as self-selected sampling (Mangifera & Mawardi, 2022), non-probability purposive sampling was applied to ensure the respondents were permanently employed as professional and managerial-level (Chin-Chin et al., 2025). A purposive sampling strategy was employed to identify participants who possessed expert knowledge of the organization's digital transformation and were actively involved in assessing its performance metrics. The inclusion criteria mandated a minimum of two years of employment with SETRAM West. The study successfully enrolled 186 subjects from a total employee population of 1,300. According to Thompson (2012) sampling formula, the minimum required sample size for this population was 53; thus, the acquired sample (n=186) is deemed statistically sufficient, including managers, department heads, and executives within the institution. 100 questionnaires were distributed during the period (between 04/03/2025 and 30/07/2025). After the data collection and sorting process, 72 questionnaires were found to be suitable for statistical analysis. The data was analyzed using descriptive statistics techniques, Partial Least Squares-structural equation modeling (PLS-SEM) and confirmatory factor analysis (CFA), and path analysis obtained through SMART-PLS.3 outputs.

More often than not PLS-SEM is presented as being a desirable multivariate data analysis method due to its remarkable ability to achieve acceptable power at very small sample sizes (Kock & Hadaya, 2018). If the model is complex the PLS-SEM works efficiently in a smaller sample size (Fornell & Bookstein, 1982).

Researchers have emphasized that PLS-SEM is particularly proficient in estimating models from an explanatory-predictive perspective, which involves understanding the links proposed in the model and its ability to foresee the theoretical constructs being studied (Ringle et al., 2023), and taking into account the mediating effects in its model design (Sarstedt & Moisescu, 2024). PLS can process various types of data and is evaluated through two primary assessments: the measurement model test, which examines construct validity and reliability, and the structural model evaluation, which focuses on the t-test related to the partial least squares method. These assessments provide a comprehensive array of detailed outcomes for rigorous analysis (Indra Siswanti & Wibowo, 2024). This methodology is based on an algorithm to estimate the specified study model by relying on both internal and external model simultaneously during the estimation process.

4. Research findings and discussion

4.1. Demographic profile

To ensure the best results and minimize bias, the sample characteristics were divided into: Gender, Age, Educational level, and Professional experience.

Table 2. Respondent Characteristics.

Characteristics	Type	Frequency	Percentage
Gender	Female	10	%13.88
	Male	62	%86.11
Age	Less than 30 years	13	%18.05
	39-30years	50	%69.44
	49-40years	6	%8.33
	More than 50 years	3	%4.16
Educational Level	Master's	10	%13.88
	Bachelor's	32	%44.44
	Secondary	30	%41.66
Professional Experience	Less than 3 years	6	%8.33
	3 to 5 years	21	%29.16
	5 to 10 years	40	%55.55
	More than 10 years	5	%6.94
Total		72	%100

We conclude from the results of table (02) that the studied sample is predominantly male, constituting 86.11% of the participants. The most dominant age group in the sample is under 40 years, representing the youth category at 69.44%. The majority of the sample has between 5 to 10 years of experience, accounting for 55.55%. Regarding educational level, the largest percentage, 44.44%, holds a Bachelor's degree.

4.2 Convergent validity

Table 3. Illustrates The Measurement Model for The Latent Variables

Latent Variables	Cronbach's Alpha	Rho-A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Digital Transformation (DT)	0.95	0.95	0.96	0.64
Employee Performance Improvement (EPI)	0.83	0.84	0.89	0.67
Enterprise Performance (EP)	0.96	0.96	0.97	0.81
Knowledge Management (KM)	0.96	0.96	0.96	0.75
Process Improvement (PI)	0.93	0.93	0.95	0.82
Service Improvement (SI)	0.92	0.92	0.94	0.8

Table (03) illustrates the results of the composite reliability coefficients for each of the variables, which are as follows:

- According to Hulland (1999), Cronbach's alpha values are considered statistically significant and acceptable if they exceed 0.70. These results are consistent with the composite reliability indicator.
- Rho de Joreskog values are considered more accurate than Cronbach's alpha because they incorporate errors in their calculation, according to Roussel (2002). These results are statistically acceptable because their values are greater than 0.70, according to Fornell and Larcker (1981), and thus, there is consistency with the composite reliability indicator.
- Composite Reliability values are also greater than 0.7, demonstrating the dependability of the measurement model employed.
- There is statistical significance to all Average Variance Extracted (AVE) values and acceptable because their values are greater than 0.5, according to Fornell and Lacker (1981), each latent variable is shown to explain more than 50% of its indicators. Therefore, convergent validity is achieved in this model, meaning that the questions are consistent with each other.

As a result, since all the composite reliability coefficients for the variables under study are higher than 0.7, therefore, it may be said that the measurement model used is reliable, and thus, convergent validity has been achieved in the model construction.

4.3 Discriminant validity

Discriminant validity is established when a construct is distinct from others. Using the Fornell-Larcker criterion, this is confirmed if the Average Variance Extracted (AVE) for each construct is higher than its squared correlations with all other constructs.

Table 4. Shows the correlations between latent variables.

	DT	E. P.I	E.P	K.M	P.I	S.I

Digital Transformation (DT)	0.8					
Employee Performance Improvement (EPI)	0.84	0.82				
Enterprise Performance (EP)	0.77	0.65	0.9			
Knowledge Management (KM)	0.82	0.73	0.83	0.87		
Process Improvement (PI)	0.96	0.7	0.76	0.79	0.91	
Service Improvement (SI)	0.94	0.67	0.7	0.75	0.89	0.9

As shown in table (04), the square roots of the AVE for each construct (e.g., 0.9 for EP) are higher than all its correlations with other constructs in the same row (0.77, 0.65) and column (0.83, 0.76, 0.7). In contrast, the square roots of the AVE for DT was greater than its correlation with external variables, such as EP (0.77) and KM (0.82) in this case we confirmed the HTMT index value of KM 0.87 which is less than 0.90 (Henseler et al., 2015) this indicate that DT is more correlated with their indicators than with indicators of KM , which supports its discriminant validity as an independent construct. Conversely, the correlations between DT and its determinants (e.g. EPI, PI & SI) were higher (0.84, 0.96, 0.94). This is theoretically expected, given that these determinants represent the foundational dimensions that constitute the overarching construct of DT. This result provides strong evidence for the disciminant validity of the proposed model variables have larger.

4.4 Evaluation of the structural model

Table 5. Indicators of Structural Model

Variables	R^2	R^2 Adjusted	Q^2	GOF
Employee Performance Improvement (EPI)	0.71	0.7	0.46	
Enterprise Performance (EP)	0.72	0.71	0.56	0.76
Knowledge Management (KM)	0.68	0.67	0.5	
Process Improvement (PI)	0.91	0.91	0.74	
Service Improvement (SI)	0.89	0.89	0.7	

Based on table (05), the indicators of structural model fit show that the R^2 value is statistically significant and acceptable. The elements of DT, represented by service improvement, process improvement, and employee performance improvement, explain between 0.71 and 0.91 of the variances in DT, which is a strong explanation. Additionally, the DT variable explains 0.68 and 0.72 of the variances in the KM and EP variables, respectively, which is also a strong explanation.

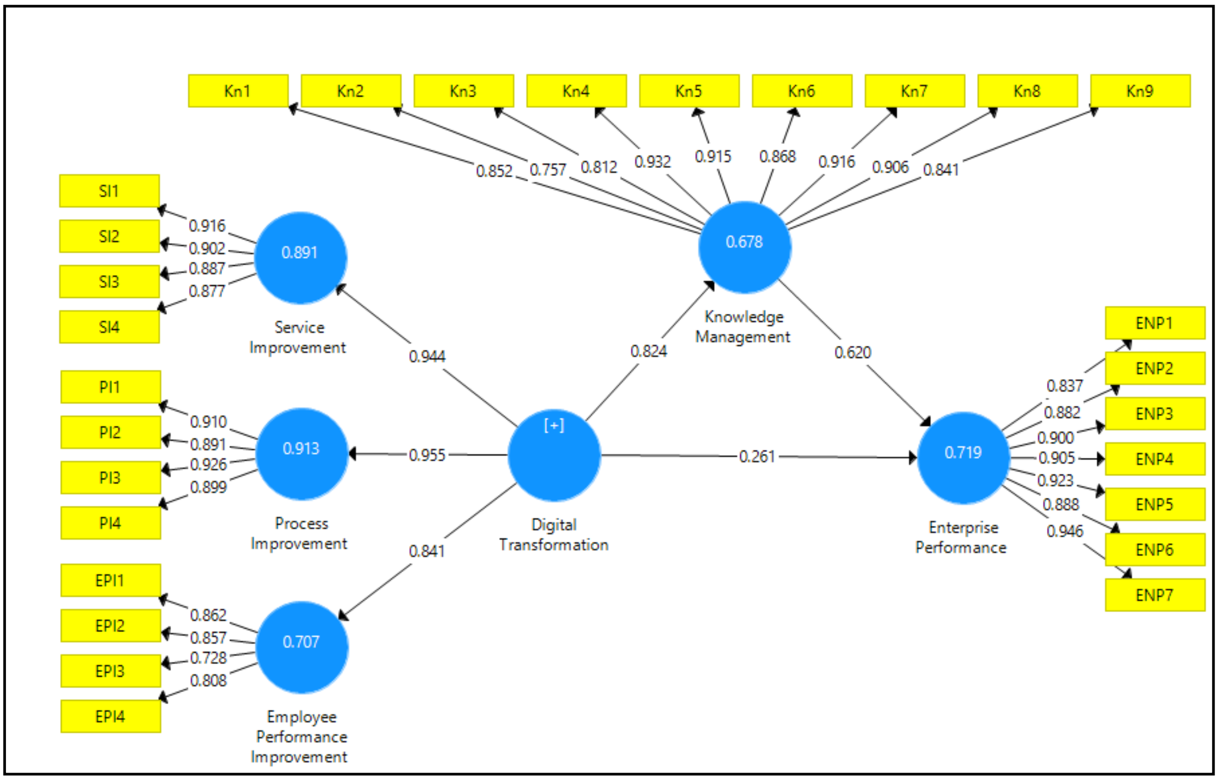
Overall, since all R^2 values for the variables are greater than 0.1 ($R^2 > 0.1$) according to Croutsche (2002), the model is statistically significant. Furthermore, the adjusted R^2 values are close to and do not differ significantly from the R^2 values, which confirm the quality and significance of the model.

Regarding the predictive quality (Q^2) value is statistically significant and acceptable because it is greater than zero according to Tenenhaus (1999), signifying that the unexpressed variables in the model has the ability to make accurate predictions. Therefore, the structural model quality index can be calculated using the following equation:

GOF = $\sqrt{(\bar{R}^2 * \overline{AVE})}$ = 0.76.

Since the GOF value is greater than 0.36 according to Wetzels et al. (2009), this denotes the caliber of the suggested structural model. The following figure shows the obtained results:

Figure 2. The final research structural model



4.5 Hypotheses Testing

The study hypotheses are tested in the table below by examining the causal relationships between the variables being investigated.

Table 6. Direct and Indirect Effects between Study Variables.

Hypotheses	Relationship	Original Sample (o)	T Statistics (|o/STDEV|)	P Values	Decision
H1	Digital Transformation > Enterprise Performance	0.261	2.1	0.04	Accepted
H2	Digital Transformation > Knowledge Management	0.824	17.13	0.00	Accepted
H3	Knowledge Management > Enterprise Performance	0.62	5.24	0.00	Accepted
H4	Digital Transformation > Knowledge Management > Enterprise Performance	0.51	5.26	0.00	Accepted

According to the data shown in table (06), we conclude that there is a direct positive impact on the correlation between the DT variable and the variable of KM, as well as the relationship between the KM variable and the EP variable, with correlation strengths of 0.82 and 0.62, respectively. These relationships exhibit statistical significance with a p-value of less than 0.05. Therefore, the second and third hypotheses were accepted. On the other hand, the relationship between the DT variable and EP appears to have a positive effect and statically significant, but it is not strong, as the correlation size was estimated at 0.2. Consequently, the first hypothesis was accepted.

Regarding the fourth hypothesis, which concerns the indirect effect between the three variables, there is a moderate positive effect estimated at 0.51, which is statistically significant, verifying the full mediation effect of DT on the relationship between EP and KM. Consequently, the fourth hypothesis was accepted.

5. Conclusions

It was the study's objective to assess the impact of DT on the EP of SETRAM, a firm, which manages tramway lines in Western Algeria, with KM as a mediating variable. The findings are as follows:

The presence of KM processes at SETRAM indicates that the enterprises place considerable emphasis on knowledge and its utilization in achieving EP, with a path coefficient of 0.620. This finding aligns with previous studies (Abu Addous et al., 2018; Dzenopoljac et al., 2018; Eid et al., 2021; Alhawamdeha, et al., 2024; Iqbala , et al., 2025). Additionally, we conducted a study to examine how KM systems affect the relationship between DT and EP, with a path coefficient of 0.51, indicating partial mediation, with KM process acting as a supporting factor. This is consistent with findings of Wang and Nianxin (2012); Sijabat (2022); Kartoyo et al.(2023); Asbeetah et al (2025). Because the impact of DT on EP was statically significant, but it is not strong, this reflects the novelty of digitalization in the transport sector, which requires new equipment and competencies to keep up with modernization. This can also be explained by the size and type of the sample, as the sample size is relatively small despite being statistically valid. Additionally, the purposive type of the current study's sample may also have an impact. Furthermore, this deliberate and well-planned approach by the tramway company toward using digital technology and keeping pace with modernization in providing services to passengers, as well as offering new services and business models tailored to their needs (such as electronic cards, payment facilities, and avenues for complaints), has contributed to a continuous increase in the number of users of the DT applications proposed by the enterprises since their implementation. This has effectively contributed to improving the company's EP, in line with the studies by Do et al. (2022); Mangifera and Mawardi (2022); Masoud and Basahel (2023); Zheng et al. (2023); Chen et al., (2024); rita and nastiti (2024). The company's director even motioned that its revenue increased by 8.12% of the total revenue for the transport company since its DT was introduced in February 2023.

DT has had a direct and positive impact that is statistically significant on KM, with a path coefficient of 0.824. This indicates that DT at the transport enterprises has significantly facilitated its KM processes. In other words, the DT, focused on improving service, operations, and employee performance at the right time and place, has enabled the surveyed employees to share and apply knowledge. Therefore, the effect reported in this current investigation is highly consistent with the findings of Machado et al., (2022); Ramírez et al. (2022); Kartoyo et al.(2023).

Consequently, it can be inferred that DT brings to more adaptability, organization, and facilitates KM processes across the organizational structures of economic enterprises in general, and specifically at the tramway transport enterprises in Western Algeria, covering the cities of Oran, Mostaganem, and Sidi Bel Abbes. These results have allowed us to form a future vision for the necessity of investing in DT and KM within economic institutions to ensure their survival and continuity in line with the economic reforms undertaken by Algeria, as well as to face competition, particularly from private urban and suburban transport companies such as the "Land Transport enterprise" and the "Railway enterprise," among other private entities.

6. Limitations and Directions for Future Research

Despite the valuable theoretical and practical contributions of this study, it is not without certain limitations that present promising avenues for future research. First, the empirical data were collected exclusively from state-owned tramway institutions in Western Algeria, which may limit the generalizability of the findings to other geographical regions or organizational contexts. Although the sample size of 72 respondents is considered adequate for structural equation modeling (SEM) using Smart PLS, it approaches the minimum threshold required for robust analysis of complex models. Consequently, the study acknowledges potential limitations associated with the sample size, including reduced generalizability and statistical power. Moreover, the use of purposive sampling may introduce potential bias (Muafi et al., 2025). Future research could broaden the conceptual framework to include a wider range of urban and semi-urban transport institutions across different regions of Algeria.Second, this study did not address the dimensions of knowledge management specifically, knowledge creation, sharing, storage, and application (Ode & Ayavoo, 2020; Al Hbabi & Alomari, 2020; Lopez et al., 2023) which could help clarify the mediating role of knowledge management in the relationship between digital transformation and organizational performance. Therefore, it is recommended that future studies integrate these dimensions along with other variables such as innovation and corporate social responsibility to enhance the explanatory and predictive power of the proposed model. Finally, the current study did not examine the influence of demographic characteristics such as gender, years of experience, and age, which may represent significant moderating factors worthy of investigation in future research.

7. References

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