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Designing a digital transformation model with an industrial development approach

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Abstract

Digital transformation is a key driver of growth and success in today's competitive environment. This applied research follows a mixed-methods approach (qualitative-quantitative). In the qualitative phase, semi-structured interviews with experts were conducted, and data was coded using Max QDA, leading to the development of an initial model based on Strauss and Corbin's framework. In the quantitative phase, the model's relationships were evaluated using ISM methodology and analyzed with PLS software. The proposed model has five primary dimensions: human capital management, digital strategy development, sales and marketing, innovative production, and service development. These dimensions are linked to contextual elements such as regulations, culture, organizational structure, and value creation. The findings highlight that digital transformation, supported by advanced technologies, enhances output growth, productivity, cost reduction, and product quality in traditional industries, ensuring industrial development and sustainability.

Keywords: Digital transformation, technology, industrial development, industry

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1- Introduction

Historical developments and globalization have emphasized the need for process changes across industries. Intense competition, constant innovation, and the widespread adoption of the internet have made digital resources the backbone of global economies. Around 38% of organizations cite technological transformations as the most influential factor in business decisions. Digital transformation (DT) involves fundamental changes in operational models and strategies, enhances operational efficiency, improves products and services, and aligns with customer demands. This transformation relies on innovations such as Artificial Intelligence (AI), the Internet of Things (IoT), Virtual Reality (VR), and Big Data (Najafi et al., 2022).

Digital transformation drives organizations to redesign processes, structures, and business models. With the emergence of Industry 4.0, companies have adopted digitalization in manufacturing processes, leveraging automation and advanced technologies like cyber-physical systems and simulation. Digitalization creates opportunities for innovation, improves productivity, reduces costs, and enables market adaptability. However, the rapid pace of technological changes presents challenges, such as the need for new skills and cultural adaptation.

Digitalization provides new opportunities for designing innovative products and services, enabling companies to predict better customer needs through data analysis. This process is supported by advanced technologies such as Machine Learning (ML), Blockchain, and Cloud Computing. Digital transformation enhances organizational performance and profoundly impacts value chains and competitive environments (Tavakkoli-Moghaddam et al., 2024).

The COVID-19 pandemic has accelerated the pace of digital transformation. Rapid technological advancements challenge manufacturing firms, requiring strategic reassessment, structural redesign, and adaptation to new conditions. By integrating digital technologies into production processes, resource management, and supply chains, digital transformation enables more efficient resource allocation and promotes sustainable development.

Many industries, particularly small and medium-sized enterprises (SMEs), still lack the necessary resources and expertise to embrace digitalization. To succeed in the digital age, these companies need clear strategies, infrastructure redesign, and intelligent use of technologies. Digitalization can enhance industrial competitiveness and drive economic growth.

Research indicates that digital transformation improves organizational operations and brings about profound changes in customer interactions and supply chains. Employing smart technologies helps companies implement more effective innovations and better respond to evolving market demands.

Ultimately, to leverage digital transformation opportunities, organizations must redesign their business models and develop innovative strategies for industrial development. These models should incorporate data analysis, agility, and flexibility capabilities. Digital transformation is no longer a choice; companies must achieve a competitive advantage and adapt to a changing environment.

2- Literature Review

Research on digital transformation (DT) in Iran is limited due to the topic's novelty, and no comprehensive model for industrial development has been proposed. Additionally, gaps exist regarding the implementation and execution of DT, as many managers lack sufficient familiarity with the process. Internationally, more studies have been conducted, but these focus on specific aspects of business models without holistic integration. For instance, Effenthaler and Egloffstein (2019) emphasized environmental and organizational factors, Guinan et al. (2019) focused on individual factors, and Queiroz et al. (2019) examined supply chains.

Previous studies in the services sector reveal DT's significant role in value creation and altering value chains. For example, Park and Kim (2020) explored the importance of shifting to customer-centric strategies using technology, while Kim and Kim (2021) identified DT as a driver for changing the insurance value chain. In education, Siljebo (2020) and Lee & Lee (2021) investigated the impact of digitization on learning and teaching methods.

According to Martin Pena et al. (2018), DT is reshaping business models and necessitating new operational strategies. Gobel (2018) highlighted the influence of digital technologies on process innovations, and Lee & Reha (2022) demonstrated DT's positive effects on operational processes in manufacturing and service industries.

Despite advancements, DT trends are not fully explored, and a comprehensive model for industrial development is lacking. Consequently, further studies are required to identify key factors and integrate digitization into the industrial sector. This study develops its conceptual framework qualitatively, refining it during data collection.

DT enables companies to enhance productivity and automate manual processes through real-time data and digital tools. However, its adoption requires employees with new competencies and clear strategies to prioritize digital transformation initiatives.

Overall, research indicates that DT serves as both a driver of industrial development and a foundation for organizational transformation and improved management. However, gaps remain in understanding DT's impacts on socio-economic structures and managerial practices comprehensively.

3- Research Methodology

Qualitative Research Methodology

This study was conducted in two phases (qualitative-quantitative). The grounded theory method was employed in the first phase to design the model. Semi-structured interviews with subject matter experts were conducted to identify the concepts and components of digital transformation and industrial development. The purpose of this phase was to recognize initial concepts and components. Semi-structured interviews were chosen because they allow the exchange of ideas and perspectives while enabling the researcher to steer the discussion toward achieving the research objectives.

Given the research topic, the statistical population for this phase consisted of specialists, experts, managers, and thought leaders in the primary domains of the study constructs. These experts were required to have knowledge and understanding of digital transformation and industrial development. Potential candidates for the interviews could include the following individuals:

Characteristics of Interviewees:

- Practitioners in the field of digital transformation.
- Active businesses in the domain of digital transformation.
- Policymakers and executive managers involved in digital transformation initiatives.
- Academic faculty members engaged in industrial development research.
- Specialists in digital transformation and industrial development.

In the preliminary phase, 19 interviews and one focus group discussion involving five participants were conducted to gather insights from experts in the field. The interview process was designed so that the data was coded and analyzed after each interview. This approach allowed for identifying dimensions raised by initial experts, which were then followed up in subsequent interviews. In this study, it was observed by the 16th interview that findings were becoming repetitive, and to ensure reliability, two additional interviews were conducted.

The expert panel method was employed in the main research phase, where five specialists participated in the data grouping process. Typically, sampling in qualitative research is non-probabilistic and purposive. In this approach, the researcher selects the sample based on their knowledge and familiarity with the population. This study utilized theoretical sampling, and a purposive sampling approach was adopted to select qualitative research participants. Additionally, the **snowball sampling** method, a subset of sequential sampling, was used to identify and choose experts. In this method, the researcher identifies participants through referrals provided by previously identified experts (Hooman, 2012).

The validity and reliability of the research indicate that the methods and procedures employed during the interviews measure precisely what they are intended to assess. Below is a detailed explanation of each aspect.

The **validity** of the data collection tool in the qualitative section (interview protocol) was evaluated through expert judgment. For this purpose, several academic experts were asked to provide feedback on the interview protocol questions' clarity, content, and comprehensiveness.

The percentage agreement method between two coders was used to assess the interview protocol's reliability. Initially, a research collaborator with experience in qualitative data coding was invited to participate in the study. Three interviews were selected from the collected data and independently coded by the researcher and the research collaborator. Based on this assessment, the reliability coefficient for the interview protocol in this study was found to be at an acceptable level, according to the researchers. The minimum acceptable value for the reliability coefficient is 0.6 (60%).

Quantitative Research Methodology

In the second phase, ISM (Interpretive et al.) and structural equations using PLS3 software were applied to test the model derived from the first phase.

The statistical population of this study consisted of expert managers from petrochemical companies. Expertise refers to individuals with over 10 years of work experience, at least a bachelor's degree, and positions of expert level or higher within petrochemical companies. Various formulas are used to calculate the sample size in social research. In this study, the sample size was determined based on the number of observable variables:

$$\mathbf{5Q < n < 15Q} \tag{1}$$

Using this formula, the sample size was estimated at 100 managers. (Considering the drop in the number of valid responses due to improperly filled questionnaires, 90 questionnaires were ultimately validated for analysis.)

Data collection in the quantitative section was conducted using a questionnaire derived from the qualitative data analysis. A researcher-developed questionnaire was used for exploratory factor analysis. The questionnaire items were drafted based on coding extracted from qualitative interviews and developed into an initial questionnaire format. Although there is no universal agreement on the sample size required for factor analysis, the sampling adequacy for exploratory factor analysis was evaluated using the **Kaiser-Meyer-Olkin (KMO)** measure. The KMO value was 0.845, and the significance level based on Bartlett's test was 0.000. These values indicate that the sample size is sufficient for conducting factor analysis, ensuring the appropriateness of the data for the analysis.

Interpretive Structural Modeling (ISM) was employed for factor analysis. Since the questionnaire was developed by researchers, its items were derived from coding qualitative interviews. The content validity of the questions was assessed by seeking feedback from domain experts, academic professors, and specialists. Initially, questions were drafted based on multiple interviews and evaluated using **CVI (Content Validity Index)** and **CVR (Content Validity Ratio)** forms.

Questions with a CVR score above 0.6 (given a panel of 10 experts) were retained, while those with a CVR score below this threshold were excluded from the questionnaire. Additionally, CVI was calculated to enhance the questionnaire's validity, and all items achieved a CVI score above 0.80, indicating satisfactory content validity.

Cronbach's alpha was utilized to evaluate the reliability of the research. This statistic ranges from 0 to 1, with higher values indicating more excellent scale reliability. According to the rule of thumb, Cronbach’s alpha should be at least 0.7 to demonstrate that the scale is reliable.

4- Research Finding

To address the first, second, and third research questions, a qualitative research methodology was employed. Grounded theory, consisting of three coding stages: open, axial, and selective coding, was utilized.

Open Coding

In the first stage (open coding), a two-step process was followed. Initially, qualitative data derived from 19 semi-structured interviews were analyzed. Using the extracted codes from these interviews conducted with domain experts, 156 initial codes were identified. Since the aim was to design a digital transformation model with an industrial development approach, the experts were asked to review these 156 codes, select relevant ones, and eliminate duplicates. As a result, over 50% of the experts agreed on 110 codes, finalized in a focus group session involving five experts.

Axial Coding

In the second stage (axial coding), the initial codes were consolidated into secondary codes due to the large number of codes. Similar codes were grouped into categories, with several secondary codes combined into a single conceptual code. At this stage, the experts were asked to classify codes of the same type into distinct groups during a focus group session. Simultaneously, the experts screened and determined the importance of each indicator.

Selective Coding

In the third stage (selective coding), following Strauss and Corbin's model, the identified components were categorized into specific themes. During this stage, a **central category** was determined, representing the core factor that explains the most significant variations and is most closely related to other categories. This central category connects all other components within a systematic structure and is expressed as a cohesive narrative, becoming a fundamental element of the model.

This structured approach ensured the digital transformation model was systematically developed and aligned with industrial development objectives.

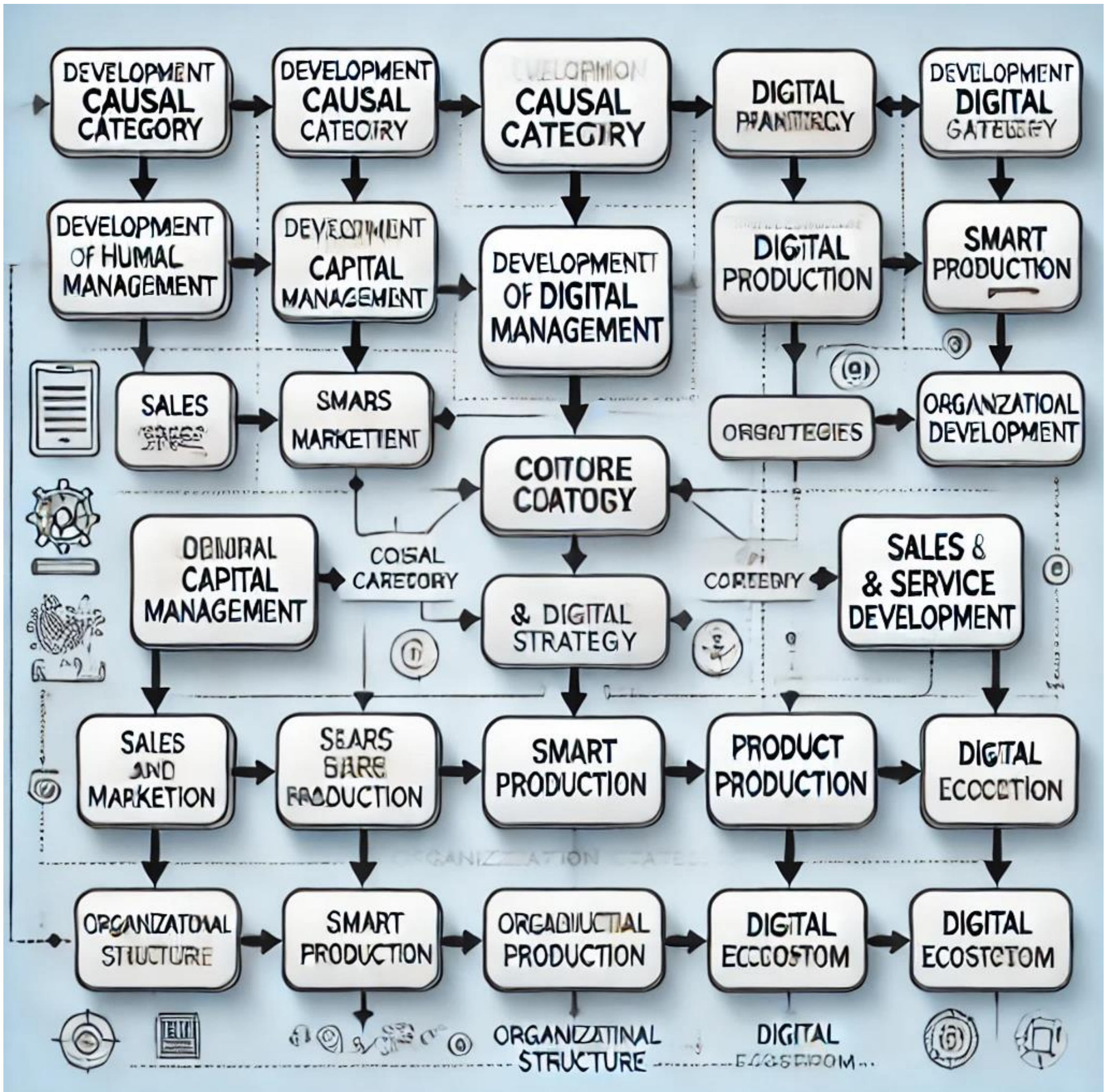

Figure 1: Qualitative research stage model according to Strauss and Corbin's method

In this study, the relationships between factors were determined based on the opinions of 14 experts. Eight of these individuals were university professors, while the rest were professionals active in digital transformation and industrial development. Experts were asked to evaluate each pair of criteria and express their opinion on whether a relationship exists between them.

Before conducting factor analysis, it is essential to ensure that the available data are suitable for exploratory factor analysis. For this purpose, the KMO index and Bartlett's test are used. Based on the significance level, it was concluded that the data are suitable for sampling and factor analysis.

Table 1: Adequacy index

KMO Index	0.814
Chi-square Statistic	442.416
Degrees of Freedom	10
Significance Value	0.000

The KMO statistic was calculated to be **0.845**, indicating that the sample size is sufficient for factor analysis. Additionally, the significance level of Bartlett's test is **0.000**, confirming that the results are statistically significant.

Validation and Model Testing

Structural equation modeling (SEM) was employed to test the validity of the theoretical research model and calculate impact coefficients. The Smart PLS method was used to evaluate the goodness of fit and validity of structural equation models, covering three aspects: measurement models, structural models, and the overall model.

Measurement Model Fit

Factor Loadings: Factor loadings equal to or greater than **0.4** indicate that the variance between a construct and its indicators is greater than the measurement error variance, suggesting acceptable reliability for the measurement model (Holland, 1999).

Cronbach's alpha, composite reliability: Given that the appropriate value for Cronbach's alpha and composite reliability is 0.7, and according to the findings in the table below, these criteria have adopted an appropriate value for the variables, it can be confirmed that the research's reliability status is appropriate.

Convergent validity: The next criterion for examining the fit of measurement models is convergent validity, which is shown by AVE and examines the degree of correlation of each construct with its questions. The higher the degree of this correlation, the greater the fit. Considering that the appropriate value for AVE is 0.5 and according to the findings of the above table, this criterion has adopted an appropriate value for latent variables, the appropriateness of the convergent validity of the research is confirmed.

Divergent validity: Fornell and Larker (1981) have suggested comparing the square root of each construct's AVE with the values of the correlation coefficients between the constructs to examine the divergent validity. As can be seen in the table below, the values of the main diameter of the matrix (the square root of the AVE coefficients of each construct) are greater than the lower values (the correlation coefficients between each construct and other constructs), and this indicates that the divergent validity of the constructs is acceptable.

Structural Model Fit

R^2 Criterion (Explained Variance):

R^2 is a criterion that indicates the influence of an exogenous variable on an endogenous variable. The values of **0.19**, **0.33**, and **0.67** are considered benchmarks for weak, moderate, and strong R^2 values, respectively. According to the table below, the R^2 values for the endogenous constructs of the study have been calculated. Based on the benchmark values, the structural model fit is confirmed as strong.

Table 2: R^2 Values for Endogenous Constructs

Variable	R^2
Digital Transformation with an Industrial Development Approach	1

Q^2 Criterion (Predictive Power of the Model):
This criterion indicates the model's predictive power. If the Q^2 value for an endogenous construct is 0.02, 0.15, or 0.35, it indicates weak, moderate, and strong predictive power, respectively, for the associated exogenous constructs. The table below shows that the model's predictive power for the endogenous constructs is strong, confirming the structural model fit.

Table 3: Q^2 Criterion for Endogenous Constructs

Variable	SSO	SSE	$Q^2 = 1 - SSE/SSO$
Digital Transformation with an Industrial Development Approach	**1456.000**	**700.368**	**0.519**

Redundancy Criterion:
This criterion measures the quality of the structural model for each endogenous variable based on its measurement model. It is calculated as the product of constructs' shared values (communality) and their corresponding R^2 values. It reflects the extent to which one or more exogenous constructs influence the variability of the indicators of an endogenous construct. Higher redundancy values indicate a better structural model fit in the research.

Table 4 : Redundancy criterion

Variables	Redundancy
Digital Transformation with an Industrial Development Approach	0.580

Overall Model Fit

Gof Criterion (Goodness of Fit Based on Partial Least Squares):
Researchers assess the overall model fit after evaluating the measurement and structural model fit. The values **0.01**, **0.25**, and **0.36** are benchmarks for weak, moderate, and strong model fit, respectively. Based on the calculated GOF value of **0.839**, the overall model fit is confirmed to be strong.

Table 5: Overall Model Fit

Variables	R^2	Communalities
Digital Transformation with an Industrial Development Approach	1	0.580
Causal	-	0.693
Contextual	-	0.915
Intervening	-	0.841
Outcomes	-	0.684
Strategies	-	0.514
Average	1	0.704

GOF: 0.839

Path Coefficients and T-statistics

The following diagrams illustrate the path coefficients and T-statistics for the research model. Path coefficients indicate the strength of the relationship between two variables. For the path coefficient to be statistically significant, the T-statistic must exceed **1.96**.

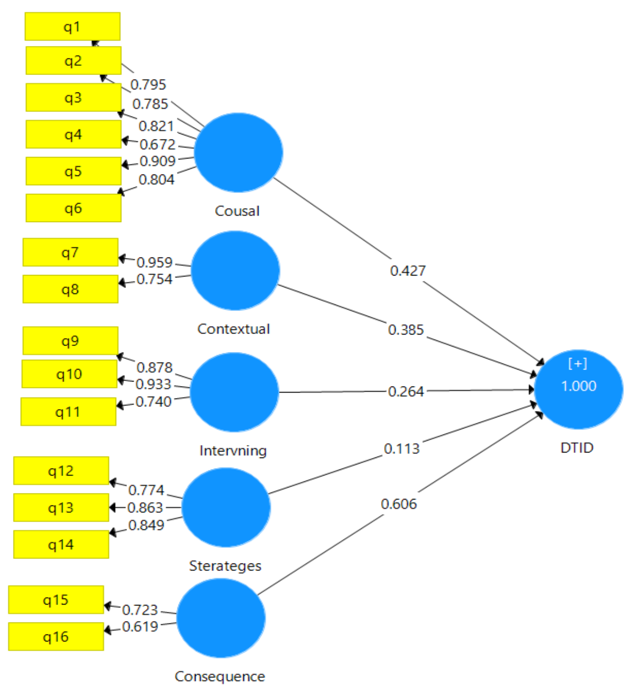

Figure 2: Path coefficients of the research model

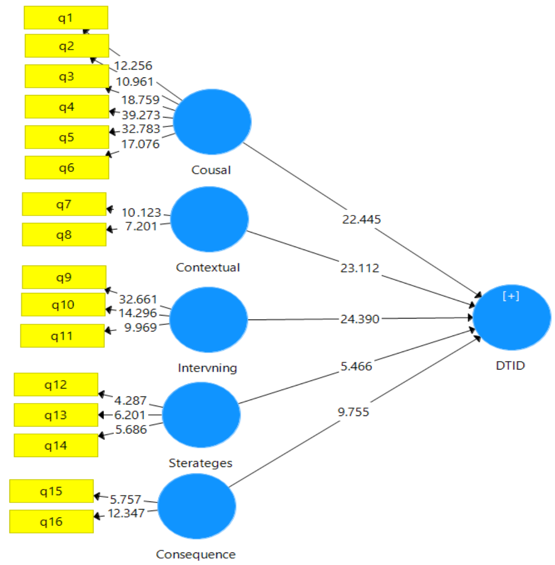

Figure 3: T-statistic coefficients of the research model

Table 6: Research Hypotheses

Hypotheses	Path Coefficient	T-statistic (>1.96)	Result
Causal Conditions → Digital Transformation with an Industrial Development Approach	0.427	22.445	Accepted
Contextual Conditions → Digital Transformation with an Industrial Development Approach	0.385	23.112	Accepted
Intervening Conditions → Digital Transformation with an Industrial Development Approach	0.264	24.390	Accepted
Outcomes → Digital Transformation with an Industrial Development Approach	0.113	5.466	Accepted
Strategies → Digital Transformation with an Industrial Development Approach	0.606	9.755	Accepted

The diagrams show that the path coefficients and T-statistics are greater than **1.96**. Therefore, all hypotheses are confirmed.

5- Conclusion

This study aims to design a digital transformation model with an industrial development approach. The final model, developed using the Strauss and Corbin method, encompasses various dimensions such as human capital management, digital strategy, smart production, marketing and sales, product and service development, and the digital ecosystem. Key strategies focus on communication, agility, and decentralization, while outcomes emphasize organizational structure and value creation.

To succeed in digital transformation, managers must first develop and align their organization's digital vision with overall strategies. It is crucial to evaluate capabilities, estimate required resources, and identify potential partnerships to achieve objectives. Digital transformation requires a comprehensive model that addresses all its dimensions.

In this study, data were collected through interviews with managers at different levels. Four key tensions were identified: the conflict between hardware and software logic, the depth of business model changes, dual goals (efficiency vs. transformation), and the scope of transformation (limited or extensive). These tensions add to the complexity of digital transformation in the industry.

Additionally, government regulations and organizational structures can influence innovation. Countries must establish high-quality infrastructures to support digital transformation. In developing countries, leveraging both indigenous and imported technologies can enhance technological capabilities.

Digital transformation in manufacturing industries faces challenges such as resistance to change, a lack of digital skills, and system integration issues. Nevertheless, digitalization presents opportunities to improve productivity, reduce costs, and enhance product quality. Industrial companies must address these challenges through organizational agility, skill enhancement, and robust data management.

For a successful digital transformation, industries should create a technological roadmap and develop talent to bridge skill gaps. Employing agile methods for implementing digital projects and equipping environments with modern technologies is essential. Managing and enriching data and creating integrated infrastructures are also key elements.

Ultimately, digital transformation requires a strategic approach that aligns organizational culture and structure with technology. Collaborating with external partners and leveraging experiences from other industries can accelerate this transformation. Future research should focus on case analyses and identifying critical factors driving digital transformation.

By addressing these dimensions, industries can harness the transformative power of digital technologies to drive innovation, improve operational efficiency, and remain competitive in a rapidly evolving landscape. This integrated approach ensures alignment between technological advancements and organizational capabilities, enabling industries to achieve sustainable growth and development.

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