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A Measurement Model Bridging Digital Technologies and Emerging Workforce Competencies for a Carbon Neutral Economy

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ABSTRACT

In accordance with SDG 13 which focuses on climate action, this study explores how digital technologies and emerging workforce competencies can support the transition toward a carbon-neutral economy. The research focused on developing and validating a measurement instrument specifically for the Saudi context. A pilot survey with 30 participants assessed item clarity and dimensionality using exploratory factor analysis in SPSS 31, identifying three key components. The main study collected 205 responses through stratified random sampling, and confirmatory factor analysis in Amos 26 confirmed the reliability and validity of the measurement model. The results demonstrate that the instrument effectively captures the relationships between digital technology adoption, workforce competencies, and carbon-neutral initiatives. By providing one of the first validated tools for Saudi Arabia, this study offers a foundation for future research and practical applications across industries, supporting strategies for sustainable development and economic transformation in line with national and global climate objectives.

Keywords: Carbon neutrality, confirmatory factor analysis, digital transformation, exploratory factor analysis, measurement model, SDG, sustainable development goals

INTRODUCTION

Saudi Arabia's pursuit of carbon neutrality under Vision 2030 has positioned both digital technologies (DT) and emerging workforce competencies (EWC) as critical enablers of sustainable transformation. Prior research demonstrates that DT, including smart grids (SG), artificial intelligence (AI) driven energy management, internet of things (IoT) monitoring systems, blockchain technology (BT) for carbon tracking, and cloud computing (CC), provide measurable mechanisms for reducing emissions, enhancing efficiency, and restructuring industrial processes (Negueroles et al., 2024). Concurrently, EWC encompassing education, technical expertise, entrepreneurship, and innovation have been shown to strengthen organizational and national capacity for sustainability by fostering innovation driven practices and low-carbon solutions (Alkofahi et al., 2024).

Despite this potential, empirical studies highlight persistent gaps. Challenges include limited digital adoption in sustainability oriented sectors, inadequate interoperability of digital systems across energy, transport, and manufacturing, as well as skill deficiencies among youth in areas such as renewable energy software, AI enabled emissions tracking, and circular economy solutions (Negueroles et al., 2024). Furthermore, regulatory frameworks for digital climate solutions remain underdeveloped (Mougayar & Buterin, 2016), and structural barriers such as insufficient investment, weak public private collaboration, and restricted funding access for green entrepreneurship constrain progress. While flagship projects like NEOM integrate advanced digital sustainability solutions, their diffusion across industries remains limited.

The Kingdom's educational reforms and government led initiatives have enhanced STEM (Science, Technology, Engineering, and Mathematics) engagement and fostered youth participation in sustainability driven innovation. However, critical structural barriers, such as the digital divide, fragmented regulatory support, and lack of targeted training continue to restrict the integration of EWC and DT in advancing carbon neutrality. This underscores the need to conceptualize and empirically validate EWC and DT as measurable constructs that function as enablers of a carbon-neutral economy (CNE). Although prior research highlights the importance of workforce competencies and digital technologies in advancing carbon neutrality, limited effort has been made to empirically operationalize these constructs or validate their measurement within the Saudi context. To address this gap, the present study adopts a two stage measurement approach: first, exploratory factor analysis (EFA) is employed to uncover the underlying dimensions of EWC, DT, and the CNE. Second, CFA is conducted to assess construct validity, reliability, and overall model fit. Accordingly, the study is intending to address the following research questions:

1. What underlying dimensions of DT, EWC, and CNE can be identified through EFA?
2. How effectively can CFA validate the reliability and model fit of these constructs?

This study adopts a research approach to design and validate a measurement model that bridges DT and EWC in advancing a CNE. This research study integrates insights across different fields, such as digital, human resource management, and environmental sustainability with cross-cutting impacts on economic and social dimensions by incorporating the perspectives of industrial practitioners and policymakers. This integration ensures that the proposed model is not only theoretically rigorous but also practically relevant to the Saudi Vision 2030 sustainability agenda and global climate action goals. This process underscores the essence of multidisciplinary research by generating knowledge that transcends disciplinary boundaries and is directly applicable to real-world challenges such as climate change and economic transformation.

LITERATURE REVIEW

Theoretical Background and Measurement of Constructs

DT have emerged as pivotal enablers in advancing a CNE, offering measurable mechanisms for sustainability. Contemporary DT such as artificial intelligence (AI), machine learning (ML), blockchain technology (BT), Internet of Things (IoT), cloud computing (CC), and big data analytics facilitate efficiency, energy optimization, and low-carbon innovations across multiple sectors (Negueroles et al., 2024). These technologies provide measurable outputs such as improved energy efficiency, carbon emissions tracking, renewable energy integration, and enhanced operational performance (Dwivedi et al., 2022. For example, BT based monitoring, reporting, and verification (MRV) enables transparent carbon credit management and supports circular carbon economy practices (Ecklu & Thomas, 2025). IoT facilitates real-time data collection and optimization in manufacturing, transport, and smart city applications, while CC and AI allow predictive energy management, system integration, and decision-making for sustainable urban and industrial operations (Cao et al., 2022; Zhu et al., 2022).

EWC are equally critical, encompassing education and skill development (ESD), entrepreneurship and innovation (EI), employment opportunities (EO), global competitiveness (GC), and social and economic equity (SEI) (DiMaggio & Hargittai, 2023; Schwab & Zahidi, 2020; Nambisan, 2017). These constructs can be operationalized through measurable indicators such as digital literacy, technical expertise in renewable energy and AI applications, entrepreneurial engagement, participation in global digital platforms, and equitable access to technology (Huisman, 2021; Qureshi, 2020). Similarly, the CNE can be measured through outcomes related to renewable energy adoption, energy efficiency, circular carbon economy implementation, green innovation technology, and policy and awareness support (Hafeez et al., 2025; Liu, et al., 2022; Yi, et al., 2024; Mirza et al., 2024; Hoque & Lee, 2025; Porwol et al., 2016; Macintosh, 2004). Prior research has developed initial frameworks for these constructs, yet empirical validation, particularly through factor analysis approaches, remains limited. Most studies focus on isolated dimensions either DT adoption or workforce skills without systematically measuring their combined contribution to CNE or testing the reliability and validity of measurement items across multiple constructs (Aziz et al., 2024; Khan et al., 2022).

Saudi Arabia's Vision 2030 underscores the central role of both EWC and DT as enablers of a CNE, yet empirical measurement of these constructs remains limited. While conceptual linkages are well established, measurement focused research using validated scales, indicators, and factor-analytic methods is scarce. Most studies treat DT adoption as a uni-dimensional construct measured through self-reported adoption or frequency indices, limiting cross-study comparability and construct validation (Dwivedi et al., 2022; Matos et al., 2022).

Operationalization of Digital Technologies

Studies employing factor-analytic methods to operationalize DT constructs are emerging but limited. For instance, AI, IoT, and BT have been assessed through multi-item Likert scales capturing adoption, technical competence, and system integration (Cao et al., 2022; Lee et al., 2022). Principal component analysis (PCA) and EFA have been used to identify latent dimensions such as process automation, predictive analytics, and smart monitoring (Zhu et al., 2022). Blockchain, for example, is frequently operationalized through indicators such as transaction transparency, carbon credit tracking, and MRV (measurement, reporting, verification) capabilities (Ecklu & Thomas, 2025; Frank et al., 2025). Cloud computing constructs are measured via scalability, accessibility, and energy efficiency indicators (Da Silva et al., 2023), while AI-enabled energy management is operationalized through predictive accuracy, system integration, and real-time decision support (Allal-Chérif et al., 2021; Luqman et al., 2024). Despite these examples, few studies have integrated multiple DT dimensions under a unified measurement framework relevant to sustainability transitions.

Operationalization of Emerging Workforce Competencies

The emerging workforce is critical for operationalizing digital sustainability initiatives. Constructs such as education and skill development (ESD), employment opportunities (EO), entrepreneurship and innovation (EI), global competitiveness (GC), and social and economic equity (SEI) are frequently cited (DiMaggio & Hargittai, 2023; Nambisan, 2017; Schwab & Zahidi, 2020). Measurement approaches often rely on self-assessment scales, competence inventories, or institutional proxies (e.g., STEM enrollment, digital literacy rates) (Helsper & van Deursen, 2017; Huisman, 2021). Factor-analytic studies using PCA or EFA have been applied to validate latent EWC dimensions, such as combining technical, entrepreneurial, and innovation capabilities into higher-order factors (Gonzales, 2016; Qureshi, 2020). CFA has occasionally been employed to confirm reliability and factorial validity, though integration with DT constructs remains rare.

Operationalization of Carbon-Neutral Economy

CNE related constructs include renewable energy adoption (REA), energy efficiency and conservation (EEC), circular carbon economy (CCE), green innovation technology (GIT), and policy and awareness support (PAS) (Hafeez et al., 2025; Liu et al., 2022). Measurement scales are typically derived from environmental performance indicators, energy consumption metrics, and survey-based assessments of green innovation adoption (Dzwigol et al., 2024). Few studies have validated these scales using PCA, EFA, or CFA, particularly in the context of integrating human capital and digital adoption as enablers of sustainability transitions (El Zein & Gebresenbet, 2024).

Although DT and EWC are increasingly recognized as key drivers of carbon neutrality, several critical gaps remain in the literature. While conceptual frameworks suggest that technologies such as AI, IoT, BT and CC can reduce emissions and enhance sustainability, empirical evidence quantifying their specific contributions in national contexts like Saudi Arabia is limited (Matos et al., 2022). Similarly, research on EWC tends to be largely qualitative, often lacking operationalized constructs and measurable indicators for skills such as digital proficiency, entrepreneurship, and inclusive workforce participation. Moreover, the interaction between DT adoption and workforce competencies in supporting a CNE remains underexplored, leaving the combined effects of technology and talent largely unexamined (Lee et al., 2024).

Existing measurement approaches also exhibit notable limitations. Psychometrically validated instruments that capture DT, EWC, and CNE collectively are scarce, resulting in fragmented assessments that examine these constructs in isolation. While techniques such as PCA, EFA and CFA have been applied to individual constructs, few studies employ an integrated approach to develop and validate comprehensive measurement models. Contextual factors, including Saudi Arabia's evolving workforce, ICT adoption patterns, and national carbon-neutral initiatives, are frequently overlooked, limiting the applicability and generalizability of prior findings (Dwivedi et al., 2022). These gaps underscore the need for research that establishes a unified, empirically validated framework to examine the interplay between DT and EWC in advancing a CNE. By adopting robust factor-analytic techniques such as EFA and CFA, such studies can operationalize key constructs, enhance comparability across research, and provide practical insights for policy formulation, workforce development, and strategic investment in digital infrastructure aimed at supporting sustainable transitions.

The below table 1, provides the structured table summarizing the constructs, indicators, scales, factor analytic methods, and measurement gaps identified from the literature.

Table 1: Structured table with summary of constructs, indicator, measurement scale and gaps

Construct	Sub-Dimensions / Indicators	Measurement Scale / Method	Factor-Analytic Approach	Key Measurement Gaps

Digital Technologies (DT)	AI/ML: predictive accuracy, energy management, optimization, smart decision-making	Multi-item Likert scales, system performance logs	EFA/PCA to identify latent factors; limited CFA (Allal-Chérif et al., 2021; Lee et al., 2022)	Mostly technical measures; rarely integrated with workforce and sustainability; limited validated scales
	IoT: real-time monitoring, emissions tracking, smart cities, climate-smart agriculture, Internet of Vehicles (IoV)	Likert scales, sensor/usage data	EFA/PCA (Akpakwu et al., 2018; Mishra et al., 2019); CFA limited	Measures often isolated; integration with DT or EWC constructs limited
	Blockchain Technology (BT): carbon credit tracking, MRV, transparency, decarbonization investment support	Likert scales, adoption indices	EFA (Ecklu & Thomas, 2025; Frank et al., 2025); CFA rarely applied	Context-specific; rarely integrated with workforce competencies and sustainability outcomes
	Cloud Computing (CC): scalability, resource efficiency, energy optimization, service accessibility	Likert scales, usage/performance logs	EFA (Da Silva et al., 2023; Q. Zhang et al., 2023); CFA sparse	Limited cross-sector validation; rarely linked with EWC or CNE
	Cybersecurity (CS): energy-proportional operations, secure digital infrastructure	Surveys, technical assessment	EFA/PCA used occasionally (Pan et al., 2015)	Rarely integrated with DT or CNE; empirical validation limited
Emerging Workforce Competencies (EWC)	Education & Skill Development (ESD): STEM education, digital literacy, technical expertise	Self-assessment scales, competence inventories, institutional proxies	EFA/PCA to identify latent dimensions (DiMaggio & Hargittai, 2023; Huisman, 2021); CFA occasionally applied	Few validated scales; integration with DT and CNE constructs minimal
	Employment Opportunities (EO): digital job access, online recruitment, gig economy participation	Surveys, employment data proxies	EFA (Lutz, 2019; Gonzales, 2016); CFA limited	Largely perception-based; few cross-sector studies

	Entrepreneurship & Innovation (EI): startup growth, innovation adoption, market access, venture capital acquisition	Multi-item Likert scales, startup performance metrics	EFA (Nambisan, 2017; Qureshi, 2020); CFA rarely applied	Rarely integrated with DT; limited longitudinal validation
	Global Competitiveness (GC): digital proficiency, international competitiveness, workforce productivity	Survey indices, national statistics	PCA/EFA occasionally (Schwab & Zahidi, 2020)	Few empirical validations at individual and organizational level
	Social & Economic Inequality (SEI): digital inclusion, access to resources, income equality	Surveys, socioeconomic indicators	PCA/EFA used in social studies (Helsper & van Deursen, 2017)	Measurement rarely linked to sustainability outcomes; integration with DT and CNE limited
Carbon-Neutral Economy (CNE)	Renewable Energy Adoption (REA): solar, wind, biomass adoption, smart grid integration	Energy usage metrics, survey items	PCA/EFA to extract latent factors (Hafeez et al., 2025; Yi et al., 2024)	Rare integration with DT and workforce measures; few validated multi-dimensional scales
	Energy Efficiency & Conservation (EEC): energy reduction, building efficiency, consumption monitoring	Energy data, Likert-type surveys	EFA/PCA (Zahid et al., 2025; Mirza et al., 2024)	Fragmented; few studies combine with DT or EWC
	Circular Carbon Economy (CCE): recycling, reuse, refabrication, digital monitoring	Surveys, process metrics	EFA (Khan, 2022; Liu et al., 2022); CFA rarely	Few validated scales integrating DT and EWC
	Green Innovation Technology (GIT): green R&D, low-carbon technologies, innovation diffusion	Survey and performance indicators	PCA/EFA for latent factors (Guo et al., 2025; Hoque & Lee, 2025)	Mostly firm-level; rarely linked to workforce or DT adoption
	Policy & Awareness Support (PAS): e-participation, government support, citizen engagement	Likert surveys, policy indices	EFA/PCA in governance studies (Porwol et al., 2016; Macintosh, 2004)	Limited cross-sector and integrated measurement with DT/EWC

METHODOLOGY

The study used quantitative approach and collected research data using a survey questionnaire. The survey instrument was developed from the literature based on the identification of potential enablers of DT and EWC that will contribute for CNE. The data analysis conducted EFA to examine the underlying factor's structure and CFA to statistically validate the measurement model.

Data Collection Process and Survey Instrument

The study used stratified purposive sampling with expert criteria and collected data from 205 upper management employees who have better knowledge in terms of DT adoption and have sustainable initiatives on carbon reduction in Riyadh, Jeddah and Damam regions of Saudi Arabia. The survey was designed to capture perceptions on technology awareness, workforce proficiency, relevance for carbon reduction, and regulatory factors. The survey was developed using constructs from prior studies and mapped to relevant content. Example questions on AIML, BT, CC, IoT, and CS were grouped under DT, while items on education and skill development, employment opportunities, entrepreneurship and innovation, global competitiveness, and social-economic inequality were captured under workforce development. Factors related to renewable energy, energy efficiency, circular carbon practices, green innovation, and policy support were assigned to carbon-neutral initiatives. The participants were chosen from energy and utilities; manufacturing, logistic and transportation, construction and digital service provider sectors as they contribute in large scale projects in Vision 2030 requiring sustainable design. Further, CFA was conducted to validate the constructs' dimensionality and reliability, confirming their appropriateness for inclusion in the structural model.

Measurement Items

All the constructs and the measurement items used in the study were well discussed theoretically in the literature. However, as this area of study is still nascent and emerging, the items of the constructs were checked for their reliability and validity. The study identified three constructs namely DT, EWC and CN. A focused literature review on these three constructs formed the basis for identified enabling factors. These constructs were further refined through consultations with industry experts from energy and utilities; manufacturing; logistics and transportation; construction; and digital services to ensure contextual relevance. A pilot test with 30 participants was then conducted to check clarity and remove any redundancies. The industry experts rated their agreement with statements on the identified enablers using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

(1) DT: The DT towards CN were measured by five items namely BT (Ecklu and Thomas, 2025; Frank et al., 2025); IoT integration Akpakwu et al., 2017; Mishra et al., 2019).The use of CC (Da Silva et al., 2023; Zhu et al., 2022). AIML adoption (Allal-Chérif et al., 2021; Cao et al., 2022; Lee et al., 2022; Luqman et al., 2024) and CS measures (Pan et al., 2015).Example statements used "To what extent do you agree that BT enhances transparency, efficiency, and traceability in carbon management and sustainable supply chains?"; "To what extent do you agree that IoT enables real-time monitoring and optimization of energy and resource usage, contributing to a CNE?"; "To what extent do you agree that AI and ML improve decision-making, predict energy demands, and optimize processes to reduce carbon emissions?"; "To what extent do you agree that robust CS ensures the safe implementation of DT and protects sustainability related data?"; "To what extent do you agree that CC enhances data management, collaboration, and operational efficiency, thereby supporting carbon-neutral initiatives?"

(2) EWC: This construct is measured by five items, ESD (Choi et al., 2020; DiMaggio and Hargittai, 2023; Helsper and van Deursen, 2017; Huisman, 2021); EO (Gonzales, 2016; in, 2019); EI (Nambisan, 2017; Qureshi, 2020) GC (Hilbert, 2016; Schwab and Zahidi, 2020) and SEI (Huisman, 2021). Example statements used "The development of youth education and digital skills enhances the effectiveness of DT in achieving carbon-neutral goals."; "Greater EO for youth strengthen the impact of DT on organizations' sustainability and carbon reduction efforts."; "Youth-driven EI amplify the contribution of DT toward a carbon-neutral economy."; "Skilled youth help organizations leverage DT to improve GC while pursuing carbon-neutral initiatives."; "Addressing SEI among youth increases the effectiveness of DT in achieving sustainable and carbon-neutral outcomes."

(3) CNE: The construct is measured by five items, REA (Hafeez et al., 2025; Khan et al., 2022); EEC (Dzwigol et al., 2024; Mirza et al., 2024; Soares et al., 2021; Zahid et al., 2025); CCE practices (Khan, 2022; Liu et al., 2022); GIT (Hoque and Lee, 2025) and PAS (Porwol et al., 2016). Example statements used "DT (e.g., IoT, AI, blockchain) accelerate the integration and adoption of renewable energy solutions."; "Smart digital tools (such as AI, IoT, and mobile apps) help optimize energy use and promote conservation practices."; "DT enhance the effectiveness of reuse, recycling, and carbon capture initiatives."; "Digital transformation fosters GIT that reduce carbon emissions."; "Digital platforms and e-governance increase public awareness and policy support for achieving carbon neutrality."

RESULTS and DISCUSSION

This study utilized the Statistical Package for the Social Sciences (SPSS) version 31 for EFA and Amos 26 for CFA. Table 1 presents the demographic characteristics of the participants. The majority are non-Saudi male, predominantly within the age group of 31 to 40, and directly employed in their respective firms. Most hold a bachelor's degree, with service-based organizations placing greater emphasis on carbon neutral initiatives through the adoption of DT.

Table 1: Profile of responding firms.

Variable	Categories	Frequency	%
Age	Below 20	26	12.68
	21-30	41	20.00
	31-40	64	31.22
	41-50	46	22.44
	Above 50	28	13.66
Gender	Male	148	72.20
	Female	57	27.80
Nationality	Saudi	81	39.51
	Non-Saudi	124	60.48
Education Level	High School	6	2.93
	Bachelor	92	44.88
	Master	80	39.02
	Ph.D.	27	13.17
Type of the firm	Product based	60	29.27
	Service based	145	70.73
Current Occupation / Role	Employee	74	36.10
	Consultant	52	25.37
	Entrepreneur	41	20.00
	Researcher	38	18.54

Exploratory Factor Analysis

EFA encompasses a set of statistical techniques designed to represent a large group of observed variables through a smaller number of latent constructs (Kim & Mueller, 1978). Its primary goal is to reduce dimensionality by clustering variables that exhibit high intercorrelations into distinct factors Tabachnick and Fidell, 2002). Within EFA, PCA is the most commonly applied method as a data reduction technique for continuous variables, identifying dominant patterns in the dataset through component scores and loading structures (Wold et al., 1987). In this study, PCA with varimax rotation was employed with fifteen measurement items to explore the factors contributing to the study. The item-total correlations ranged between 0.30 and 0.801, with all item validity coefficients exceeding the threshold of 0.30. As suggested by Tabachnick and Fidell, 2002, the analysis incorporated Kaiser-Meyer-Olkin (KMO) higher than 0.5, which resulted in 0.894 and Bartlett's test of sphericity is significant (4295.918; $p < 0.001$) and assessed the sampling adequacy and factorability conditions, scree plots, factor loadings, and total variance explained to determine the robustness of the factor structure. Components with eigenvalues exceeding 1 and variables with factor loadings above 0.5 were retained, with all items demonstrating loadings greater than 0.5 on their respective constructs ranging from 0.824 to 0.928. Table 2 demonstrates the PCA results and screen plot in figure 1. The items were also checked for any possible cross loadings to avoid problems in construct validity and measurement ambiguity in further analysis.

Table 2: Rotated Component Matrix.

Item	Statement	Component		
		1	2	3
BT	I agree that blockchain technology enhances transparency, efficiency, and traceability in carbon management and sustainable supply chains.	0.909		

IoT	I agree that IoT enables real-time monitoring and optimization of energy and resource usage, contributing to a carbon-neutral economy.	0.928		
CC	I consider that cloud computing enhances data management, collaboration, and operational efficiency, thereby supporting carbon-neutral initiatives.	0.898		
AIML	I believe that AI and ML improve decision-making, predict energy demands, and optimize processes to reduce carbon emissions.	0.923		
CS	I agree that robust cybersecurity ensures the safe implementation of digital technologies and protects sustainability related data.	0.893		
ESD	I believe the development of youth education and digital skills enhances the effectiveness of digital technologies in achieving carbon-neutral goals.		0.844	
EO	I understand greater employment opportunities for youth strengthen the impact of digital technologies on organizations' sustainability and carbon reduction efforts.		0.890	
EI	I agree youth-driven entrepreneurship and innovation amplify the contribution of digital technologies toward a carbon-neutral economy.		0.895	
GC	I trust skilled youth help organizations leverage digital technologies to improve global competitiveness while pursuing carbon-neutral initiatives.		0.897	
SEI	I agree addressing social and economic inequalities among youth increases the effectiveness of digital technologies in achieving sustainable and carbon-neutral outcomes.		0.908	
REA	I agree digital technologies accelerate the integration and adoption of renewable energy solutions.			0.850
EEC	I believe smart digital tools help optimize energy use and promote conservation practices.			0.824
CCE	I trust digital technologies enhance the effectiveness of reuse, recycling, and carbon capture initiatives.			0.883
GIT	I believe digital transformation fosters green innovations and technologies that reduce carbon emissions.			0.892
PAS	I understand digital platforms and e-governance increase public awareness and policy support for achieving carbon neutrality.			0.902
Initial eigenvalues		7.699	3.755	1.590
% of Variance		51.326	25.003	10.603
Cumulative %		51.326	76.359	86.962

Source: SPSS analysis of primary data.

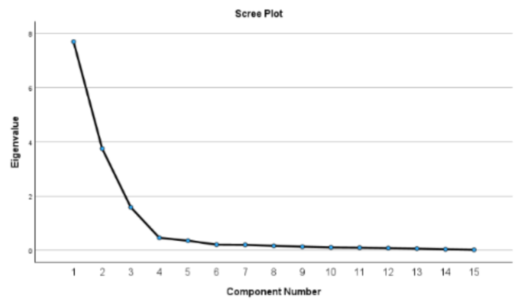

Figure 1: Factor graph for eigen values

Confirmatory Factor Analysis

CFA was conducted using AMOS version 26. The measurement model demonstrated strong construct reliability, as indicated by composite reliability (CR) values ranging from 0.940 to 0.960, exceeding the recommended threshold of 0.70 (Nunnally J.C, 1978), as presented in Table 3. The average variance extracted (AVE), which represents the proportion of variance captured by a construct relative to measurement error, ranged from 0.701 to 0.927, surpassing the 0.50 cutoff suggested by (Fornell and Larcker, 1981). As suggested by Bentler, 1980, the statistically acceptable fit indices as shown in Table 4. The overall model exhibited a good fit across multiple indices: relative χ^2 = 2.790 ($p < 0.001$), GFI = 0.901, CFI = 0.964, RMSEA = 0.080, and SRMR = 0.035. Construct validity was further assessed through convergent and discriminant validity tests. Convergent validity was supported, with factor loadings of the indicators on their respective constructs ranging from 0.760 to 0.982, consistent with the recommendations of Gerbing and Anderson, 1988. Discriminant validity was confirmed by comparing the square root of the AVE for each latent variable with the correlations between constructs, ensuring that each construct was distinct from the others.

Table 3: Reliability and Convergent Validity.

Variable / Construct	Item	Standardized Factor Loading	Cronbach Alpha	C.R	AVE
DT	BT	0.982	0.985	0.984	0.927
	IoT	0.967			
	CC	0.951			
	AIML	0.971			
EWC	CS	0.944	0.972	0.972	0.874
	ESD	0.881			
	EO	0.914			
	EI	0.937			
	GC	0.966			
	SEI	0.974			
CNE	REA	0.781	0.921	0.921	0.701
	EEC	0.760			
	CCE	0.863			
	GIT	0.883			
	PAS	0.891			

Table 4: Goodness of fit indexes for the factor structure of the scale items.

Goodness of Fit Index	Acceptable Limit	Values Obtained
X2/df	<5 moderate fit <3 good fit	2.790
Goodness of fit index (GFI)	>0.90	0.901
Comparative fit index (CFI)	>0.90	0.964
Normed fit index (NFI)	>0.90	0.945
Relative Fit Index (RFI)	>0.85	0.934

Standardized Root Mean Square Residual (SRMR)	< 0.08	0.035
Root mean square error of approximation (RMSEA)	< 0.08	0.080

As shown in the figure 2, the CFA results indicate that BT (0.98), AIML (0.97), and IoT (0.97) exhibit very high standardized regression weights with the DT construct. Similarly, GC (0.97), SEI (0.97), and EI (0.94) revealed substantial loadings on the EWC latent construct, and PAS (0.89), GIT (0.88) are potential items of CNE. This demonstrates that these items strongly contribute and are reliable indicators of the latent construct.

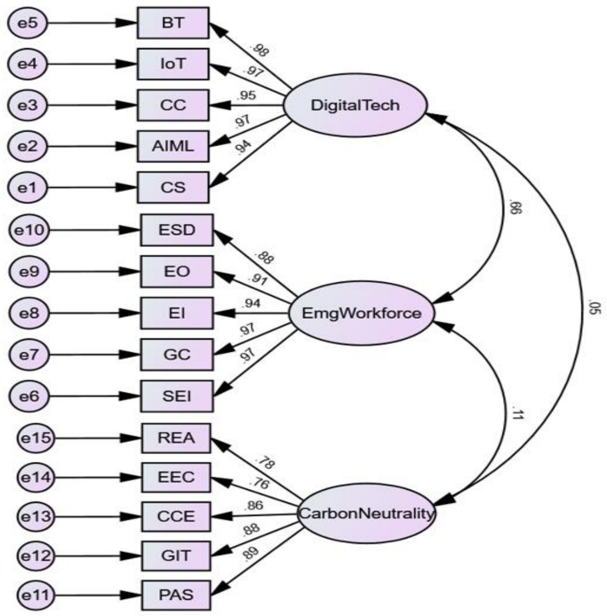

Figure 2: Measurement Model

Table 5: Correlation of the constructs.

	Relationship		Coefficient
DT	<-->	EWC	0.658***
EWC	<-->	CNE	0.111*
DT	<-->	CNE	0.049

The findings indicate that mid-career professionals in service oriented firms, predominantly non-Saudi males with bachelor's degrees, are actively engaging with DT to advance sustainability objectives. The high level of educational attainment suggests that organizations prioritize skilled personnel capable of leveraging DT to enhance operational efficiency and foster innovation, reflecting a strategic alignment between workforce capabilities and carbon-neutral initiatives. EFA confirmed three distinct but interrelated constructs DT, EWC, and CNE together explaining nearly 87% of the variance. CFA further validated the model, demonstrating high reliability and convergent validity, with strong factor loadings for key DT items (BT, AI & ML, IoT) and EWC items (GC, EI and SEI). As seen in table 5, the correlation results among the constructs between DT and EWC ($r = 0.658$, $p < 0.001$) indicates that technological adoption significantly enhances workforce competencies. In contrast, the direct relationships between DT and CNE ($r = 0.049$, $p < 0.05$) and between EWC and CNE ($r = 0.111$, $p < 0.05$) were weak but significant, suggesting that additional organizational mechanisms mediate the translation of technology and skills into tangible carbon-neutral outcomes. These results emphasize that while DT and workforce competencies are critical enablers, achieving carbon neutrality requires a coordinated approach that integrates technology, human capital development, and organizational processes. Investing in digital skills and technological education is therefore essential to accelerate Saudi Arabia's transition toward a carbon-neutral economy, promote sustainability, and support the broader objectives of Saudi Vision 2030. The findings align with prior studies highlighting the role of digitalization in circular economy practices and sustainable development (Alkofahi et al., 2024). This study underscores the strategic importance of workforce competencies and digital innovation in bridging the gap between technological potential and sustainable impact.

RESEARCH LIMITATIONS

While this study provides important insights, there are several limitations that should be considered. First, the sample was heavily skewed toward non-Saudi males aged 31–40, most of whom held bachelor's degrees and worked in service-oriented organizations. This limits the generalizability of the findings to other demographic groups, including females, younger or older employees, individuals with different educational backgrounds, and those working in product based or smaller firms. Future research should aim for a more balanced and representative sample to better reflect the diversity of the Saudi workforce. Second, although rigorous statistical methods such as EFA and CFA were employed to validate the measurement model, the cross-sectional design of the study restricts the ability to establish causal relationships among DT, EWC and CNE outcomes. Longitudinal studies or experimental designs would provide a clearer understanding of how these factors interact and evolve over time.

Finally, this study relied primarily on quantitative, organizational level data, which may not fully capture the cultural, behavioral, or contextual factors that influence carbon-neutral initiatives. The relatively weak direct correlations observed between DT and CNE outcomes, as well as between EWC and CNE, suggest the potential influence of mediating or moderating variables that were not included in the analysis. Future research could incorporate qualitative approaches, or explore additional factors such as organizational culture, regulatory frameworks, or employee engagement to provide a more comprehensive understanding of the drivers behind carbon-neutral transitions in Saudi Arabia.

CONCLUSION

This study highlights the critical role of DT and EWC in supporting Saudi Arabia's transition toward a CNE. While advanced technologies such as BT, AIML, IoT, CC and CS improve operational efficiency and promote sustainability initiatives, their direct impact on carbon-neutral outcomes appears limited. Instead, these technologies are most effective when combined with a skilled, competent workforce, emphasizing the importance of education, training, and innovation in converting technological adoption into tangible environmental benefits. The strong positive relationship between DT and EWC underscores the need for continued investment in digital skills and workforce development. By enhancing organizational capabilities, such investments can accelerate the implementation of carbon-neutral practices. Although the direct effects of workforce competencies and technology adoption on carbon neutrality were modest, they were statistically significant, indicating that broader organizational and systemic factors likely mediate these relationships. Moreover, the findings suggest that integrating advanced digital technologies with strategic human capital development is essential for improving energy efficiency, reducing carbon emissions, and achieving Saudi Arabia's sustainability and economic diversification goals under Vision 2030. By promoting technological literacy and strengthening workforce competencies, organizations can harness digitalization to drive sustainable development while building long-term economic resilience.

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