Deep Learning Readiness for Smart Manufacturing: A Socio-Technical Approach

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Abstract

The study's goal is to look into the current situation of Egyptian industrial organization's readiness to use deep learning techniques, as well as to identify both technical and social factors that influence their readiness to use advanced artificial intelligence technologies. The study employed a questionnaire to gather data from 162 factories across different industrial sectors in Egypt. The research hypothesis test was based on the structural equation modeling method, which uses the partial least squares method based on variance to analyze data through the "Smart-PLS" program. This method was chosen because it is the most appropriate for the study's characteristics, taking into account factors like sample size and data type. The results showed that enhancing the technical and social aspects of the manufacturing system has a positive impact on an organization's readiness to apply deep learning techniques in the Egyptian context, which in turn has an impact on this organization's capacity to apply smart manufacturing technologies. The study additionally found that Egyptian manufacturers are just partially ready to use deep learning techniques, with a medium readiness level, and that they continue to use manufacturing systems that are somewhat distinct from artificial intelligence technology. The study provides set guidelines to improve organization's deep learning readiness for smart manufacturing in the Egyptian industrial sector.

Key words: Deep learning; Smart Manufacturing; Socio-technical Theory; Deep learning Readiness; Egyptian industrial organizations.

Introduction

Presently, the application of cutting-edge artificial intelligence (AI) technology is changing many aspects of how industrial organizations conduct business. AI techniques, such as Deep learning (DL) and machine learning (ML), have aided smart manufacturing by increasing productivity while decreasing costs and manufacturing faults (Lee *et al.*, 2018; Chien *et al.*, 2020).

Due to the changing nature of new technology, and receiving large volumes of data that may be structured, unstructured, or semi-structured that come from various sources, as well as the development of smart manufacturing practices, which has led to an increase in the collection of data from manufacturing and production operations, which presents a challenge for organizations in their quest for the best possible solution to a problem (Votto *et al.*, 2021; Bag *et al.*, 2021).

Consequently, there was a need for technologies to assist these organizations in dealing with the challenges of processing large amounts of unstructured data, where DL techniques stand out due to their capabilities in solving more complex problems that go beyond ML techniques, as they are the most advanced version of ML algorithms, so it adopted in the manufacturing sector (Akter *et al.*, 2021; Rawat *et al.*, 2021; Salloum *et al.*, 2020).

Egypt has, like the majority of developing nations, endeavored to identify and address the issues impeding the expansion and advancement of its industrial sector (Salaheldin, 2007), with a particular focus on the manufacturing sector, which is intimately linked to the country's economic development (Salaheldin & Eid, 2007).

Egypt established a goal to achieve a gradual shift in the industrial structure from resource-based and low-technology activities to medium- and high-technology industries to develop the technological and industrial base for its manufacturing activity (Industry and Trade Development Strategy, Ministry of Trade and Industry, 2020). In an effort to step up efforts to enable artificial intelligence technologies and incorporate them into manufacturing processes (smart manufacturing), it also developed the National Strategy for Artificial Intelligence (National Strategy for Artificial Intelligence, National Council for Artificial Intelligence, 2021).

Since the adoption of AI technologies from the perspective of socio-technical theory has become increasingly common in modern intelligence research, a significant amount of research has been done on the impact of socio-technical factors on organization's adoption of AI technologies (including its sub-technique, DL and ML). However, more research is still needed (Smit *et al.*, 2023).

As a result, it is critical that the initial stage of this process identify whether or not these organizations are ready to use DL techniques. To put it another way, it's critical to recognize and appreciate these organization's level of readiness for adopting AI-related techniques, as well as to be aware of the social and technical factors that may influence how ready they are to use these cutting-edge technologies.

Literature review

Deep learning

The origins of DL may be found in 1943, when Warren McCulloch and Walter Pitts developed a computer model inspired by the neural networks seen in the human brain, as time continues, we reach the beginning of the new millennium, DL brought new life to neural network research by adding many components that made training deeper networks simple. Currently, the evolution of artificial intelligence is dependent on DL. DL is still evolving and in need of creative ideas. (Bengio *et al.*, 2021; Keith, 2022).

Deep structured learning sometimes referred to as DL or hierarchical learning has become a new field of interest in ML since 2006, DL can be defined as a subset of ML methods for pattern recognition, classification, and supervised or unsupervised feature extraction and transformation that take advantage of several layers of non-linear information processing. (Hinton & Salakhutdinov, 2006; Bengio, 2009; Deng & Yu, 2014).

The majority of research on DL focuses on developing techniques for using linear and nonlinear variables to analyze massive data sets in order to build high-degree abstractions (Arel *et al.*, 2010; LeCun *et al.*, 2015; Schmidhuber, 2015).

DL architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, convolutional neural networks and transformers have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science and material inspection, where they have produced results comparable to and in some cases surpassing human expert performance (Ciregan, 2012; Krizhevsky, 2012).

Jamwal *et al.* (2022) relied on three basic structures in DL including Auto Encoders (AE); Restricted Boltzmann Machine (RBM); Long Short Term Memory (LSTM), while Wang *et al.* (2018) relied on Convolutional Neural Network (CNN); Restricted Boltzmann Machine (RBM); Auto Encoder (AE), Recurrent Neural Network (RNN) and Model Comparison.

Organization's deep learning readiness

The ability of an organization to utilize and benefit from information technology is referred to as "IT-Readiness" (Stentoft *et al.*, 2021).while the ability of an organization to execute transformation involving AI-related applications and technology is referred to as "AI-readiness" (Alsheibani *et al.*, 2018).

Initially, Issa *et al.* (2022) used a model that depended on three dimensions—trust, challenge of the human aspect, and preference for sophisticated technology—to quantify AI-readiness. This approach was first developed by Berndt *et al.* (2010).

Schumacher *et al.* (2016) developed a model based on empirical foundations to assess industrial organizations' readiness. They established 9 dimensions and 62 factors. These dimensions included: "Products"; "Customers"; "Processes"; "Technology", "strategy" dimensions; "Leadership"; "Governance"; "Culture"; and "Individuals".

While (Stentoft *et al.*, 2021) presented seven additional dimensions that also express the organization's readiness, they did this within the context of complementing the efforts of (Haug *et al.*, 2011) to present a model to measure the organization's readiness towards information technology, which they proposed based on three basic characteristics, these dimensions included: facing pressures to change current operations; willingness to take risks to try these techniques; sufficient knowledge of these technologies; the presence of employees with appropriate competencies; the right motivation to work with these techniques; Obtaining adequate senior management support in terms of financial and administrative support.

After a review of the different measurement models, it was discovered that all of the previously discussed models address the topic of readiness from the perspective of "maturity" which means assessing the application process for these DL technologies from the point of actual implementation onward. In contrast, the current research focuses on evaluating readiness prior to engaging in implementation processes, or prior to maturity, as permitted by the Stentoft *et al.* (2021) model. As such, this model is consistent with the goals of this study.

Since AI-readiness entails more than just AI technology and the advancement of AI is based on DL, where DL is a more evolved branch of ML that uses layers of algorithms to process data and imitate the thinking process, or to develop abstractions (Curran & Purcell, 2017; Paul, 2020), therefore, "DL readiness" may be applied as AI-readiness with some modifications.

Smart manufacturing

The term "smart manufacturing" was coined by the Smart Manufacturing Leadership Coalition (SMLC) to refer to a new wave of networked data and information technology capabilities that will revolutionize manufacturing operations in the future (Davis *et al.*, 2015). Often referred to as the fourth industrial revolution, smart manufacturing is the application of a number of state-of-the-art technologies to support accurate and efficient professional decision-making (Kang *et al.*, 2016).

Zenisek *et al.* (2021) examine the challenges and lessons learnt from implementing a subset of smart manufacturing technologies such as Augmented Reality-supported Remote Assistance, Additive Manufacturing, and Predictive Maintenance.

Posada *et al.* (2015) and Roblek *et al.* (2016) describe the five major characteristics of smart manufacturing technologies as follows: digitalization, optimization, and customization of production; automation and adaptation; human-machine interaction; value-added services and stores; and automatic data exchange and communication. Hermann *et al.* (2016) identified four important components of smart manufacturing technologies: cyber-physical systems; the Internet of Things; the Internet of Services; and smart factories.

Rüßmann (2015) highlighted a set of advanced technologies that act as the basic pillars of smart manufacturing: Big Data and Analytics; Autonomous Robots; Simulation; Horizontal and Vertical System Integration; The Industrial Internet of Things; Cyber security; The Cloud; Additive Manufacturing; Augmented Reality and Industrial Internet of Things. Furthermore, Motyl *et al.* (2017) and Alcácer& Cruz-Machado (2019) agreed with Rüßmann (2015) on the key features of smart manufacturing.The same cutting-edge technologies are used by Abdullah *et al.* (2023), but with the inclusion of block chain technology and the omission of horizontal and vertical system integration.

Socio-technical systems theory

The term "socio-technical systems" was first used in work primarily by Trist and Bamforth starting in 1951, following their study of work in English coal mines. Trist & Bamforth (1951) demonstrated that the findings of their research fit into a larger project concerned with investigating ways to increase the effectiveness of information dissemination through socio-technical development in industry, under the auspices of the Tavistock Institute for Human Relations.

Since Cherns emphasized in 1976 that an organization's change must take into account both technical and social factors, the socio-technical notion has grown. Cherns (1976) is credited as being the first to create socio-technical design concepts within the context of organizational design and development.

Appelbaum (1997) discussed socio-technical systems theory as an intervention strategy for organizational development, explaining that while this strategy has many strong points, it should be used as part of a strategic change plan for organizational development rather than as a separate strategy.

Walker *et al.* (2008) also discussed the socio-technical concept, pointing to the interrelationship between social and technical systems and explaining that the socio-technical theory was founded on two main principles, the first being that the interaction of social and technical factors creates the conditions for successful systems performance, and the second being that social and technical improvement (the most common) works to increase the amount of non-linear (unexpected) relationships, the concept of " joint optimization" is central to socio-technical theory.

Consequently, a variety of industrial fields, particularly manufacturing, have embraced socio-technical systems theory as a framework for study. Murphy *et al.* (2018), Rezaey *et al.* (2020), Sovacool *et al.* (2021), Del Rio *et al.* (2022) additionally utilized socio-technical systems to investigate and improve various industrial processes.

As stated by Marcon *et al.* (2021) Sociotechnical Theory is predicated on the idea that in order for an organization to accomplish its objectives, its social and technical systems must be jointly developed while taking the environment and work organization system into account.

Deep learning readiness for smart manufacturing and socio-technical theory

Truvé & Ryfors (2019) and Chen *et al.* (2022) discussed DL as one of the tools that can be relied upon in manufacturing processes during the Fourth Industrial Revolution. Although the initial goal of implementing DL in manufacturing is to manage product quality, DL has additional advantages such as design, testing and evaluation; manufacturing; operation management; maintenance; and sustainment (Hernavs *et al.*, 2018).

Firms that rely on smart manufacturing use sensors to collect data from their sources, and DL techniques play an important role in automatically learning from data, finding trends, and making judgments. It can diagnose the root cause and describe why it occurs (Kusiak, 2017; Wang *et al.*, 2018).

According to Jamwal *et al.* (2022), there are four aspects to employing DL techniques in smart manufacturing applications: predictive maintenance; reliability analysis; quality assurance; and fault assessment.

On the other hand, the challenges to AI adoption are not confined to the technological context, but also to the organization's capabilities, organizational resources, procedures, structures, and adaptability (Alsheibani *et al.*, 2018).

Pan *et al.* (2022) discusses facilitators and constraints of AI adoption through technology, organization, and environment factors.

Cubric (2020) covers a systematic review and discusses how social variables affect the adoption of business AI. From an organizational viewpoint, Pai & Chandra (2022) examines the technological factor that affects the adoption of AI. Additionally, Wanner *et al.* (2020) use AI ML and DL technology to address the most significant elements affecting AI-based decision support systems and attempt to comprehend the technical obstacles associated with implementation.

Chatterjee *et al.* (2021) established a link between technological and social elements (internal and external environments) that impact a firm's inclination to adopt AI (DL and ML) through smart manufacturing.

Consequently, organization's adoption of artificial intelligence technologies is influenced by both social and technical factors. However, in order to fully understand the social and technical implications of attempting to adopt these technologies—particularly DL—in order to support smart manufacturing, more research is now required. This is what motivates this study to look into the aspects that determine an organization's DL readiness for applying smart manufacturing technology.

Research questions and objectives

Egypt took steps to build the industrial and technological foundation for its manufacturing sector by gradually moving toward high-technology industries. This brought attention to the degree of readiness of Egyptian industrial sector organizations for these changes, particularly in light of the sector's challenges with artificial intelligence-related technological advancements.

This research aims to explore the extent of readiness of Egyptian industrial organizations to apply DL techniques, as well as to determine the impact of both social and technical factors on the readiness of Egyptian industrial organizations to adopt the application of DL and the impact of this on the application of smart manufacturing techniques in those organizations.

Therefore, this study will address the following questions:

i. *How do technological factors influence Egyptian industrial organization's readiness to apply DL techniques?*
ii. *How do social factors influence Egyptian industrial organization's readiness to apply DL techniques?*
iii. *How does the readiness of an organization to apply DL techniques influence the application of smart manufacturing techniques in Egyptian industrial organizations?*
iv. *How ready are Egyptian manufacturers to use DL techniques, and what is their present attitude towards using smart manufacturing technologies?*

Contribution to current knowledge

This study's primary contribution is that it is the first to assess the readiness of Egyptian manufacturing companies to use DL techniques, connect them to the use of smart manufacturing technologies, and determine how widely these cutting-edge technologies are used in Egypt's industrial sector. Additionally, this study makes an applied contribution to the field of information systems research concerning operations in general and artificial intelligence technologies in particular, especially since they pertain to the use of these technologies in developing countries.

Research methodology

Hypotheses

According to the study literature and the relationship between the research variables, to identify the extent of readiness of Egyptian industrial organizations to apply DL techniques, as well as the factors (social and technical) that might affect the degree of readiness to adopt DL techniques in the Egyptian environment, it is necessary to test the following hypotheses:

H1: *Improving the technical factors of manufacturing processes has a positive impact on the organization's readiness to apply DL techniques in the Egyptian environment.*

H2: *Improving the social factors of the manufacturing system has a positive impact on the organization's readiness to apply DL techniques in the Egyptian environment.*

H3: *Increasing readiness of Egyptian industrial organizations to apply DL techniques leads to an increase in these organization's adoption of smart manufacturing techniques in the Egyptian environment.*

H4: *Egyptian industrial organizations achieve a low degree of readiness towards applying DL techniques.*

H5: *The most advanced smart manufacturing technologies are applied to a low degree by Egyptian industrial organizations.*

Figure (1) depicts the impact of "social factors" and "technical factors" on "organization's DL readiness" based on a socio-technical approach. Likewise, "organization's DL readiness" influences "application of smart manufacturing technologies".

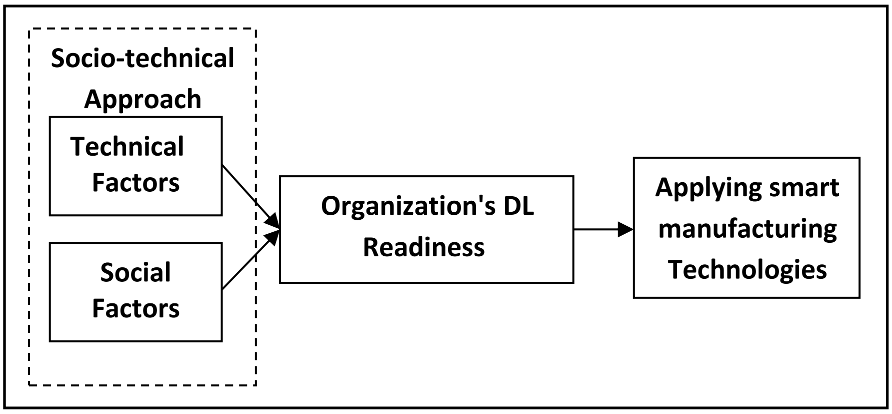


Figure (1) Proposed Study Model

SEM-PLS as a method of analysis

The structural equation modeling approach based on the Variance-Based Partial Least Squares SEM (PLS-SEM) is used to analyze the data through the Smart-PLS program to test the study hypotheses (Hair, *et al.*, 2014). This method is best suited for the specifics of this research since it takes sample size and data type into account.

The minimum appropriate sample size for the (PLS-SEM) methodology

i. This study depends on the formation of a constructive model that includes four latent variables, all of which contain reflective indicators, including three structural paths.

ii. appropriate size of sample for the proposed model can be calculated according to "ten times rule" which was declared by (Hair *et al.*, 2011; Peng & Lai, 2012) through the following steps:

   a. The number of structural paths in the model proposed in the research = 3 paths.

   b. 3 paths × 10 = 30 elements.

   c. So the expected size of the sample size is at least 30 elements.

   d. Therefore, the number of research elements is suitable for building the proposed model, as the number of elements is 32, which is greater than 30 elements (expected size).

Scales and Measurement Tools

In the first section of the questionnaire, the study used Marcon *et al.* (2021) scale to measure the variables "social factors" and "technical factors" from the European Manufacturing Survey, which is one of the largest manufacturing survey studies on the European continent.

The second section of the questionnaire included items indicated to measure "organization's DL readiness" using the Stentoft *et al.* (2021) scale. In this section, questionnaire has a five-point Likert scale and is designed as follows: (1 = Strongly agree; 2 = agree; 3 = Neither agree nor disagree; 4 = Strongly disagree; and 5 = disagree).

The third section of questionnaire contained items that meant to measuring "applying smart manufacturing technologies" relied on the Rüßmann (2015) scale. In this section, (Responses are given on a five-point Likert scale, according to the opinion of the respondent, where 5 = Very high to 1 = Very low).

Data collection

The data was gathered using a questionnaire list that was personally and electronically distributed to production and operations managers in the companies under study. The questionnaire list included 32 phrases, 6 for measuring the variable "social factors"; 7 for measuring the variable "technical factors"; ٧ phrases to measure "organization's DL readiness"; 12 phrases to measure "applying smart manufacturing technologies"; in addition to 3 items to determine the type, size, and production system used by the companies and factories in question.

The questionnaire forms were distributed in December 2021, the first set of responses were not received until late February 2022. To obtain the highest possible response rate, the questionnaires were also re-sent electronically - via "WhatsApp" program according to the phone numbers attached to the industries guide, by attaching the link to the questionnaire prepared by "Google form"-. Another group of responses was received in the beginning of November 2022; In early 2023, a set of questionnaires were received. 32 valid questionnaires, with a response rate of around 20%, were collected for statistical analysis.

Research sample

A random sample of (162) elements was chosen from various Egyptian industrial sectors, which is the statistically required size with confidence level (95%) and a standard error (5%), as specified in the electronic tables created for this purpose. The questionnaires have been distributed to production and operations managers as table number (1) represents.

The Egyptian Industries Directory, which has 279 companies registered It is under the scope of industries, which is compatible with the nature of this research, and was utilized to identify the research population, along with databases from the General Authority for Industrial Development and the Federation of Egyptian Industries.

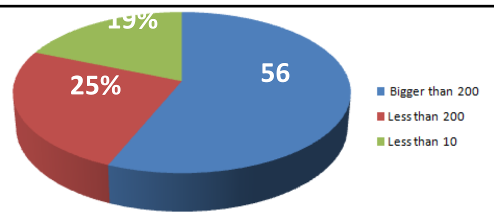
Although attempts were made to achieve higher response rates than those that were attained, the reason for this percentage is the area of study concerning the utilization of sophisticated artificial intelligence technology and the dearth of businesses that are focused on applying this technology; additionally, certain businesses declined to reply on reason that data confidentiality must be upheld.

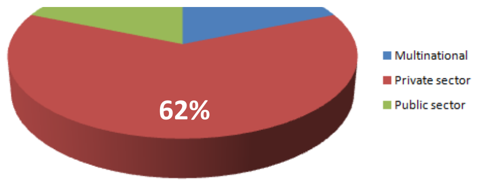
Table (1) Research sample

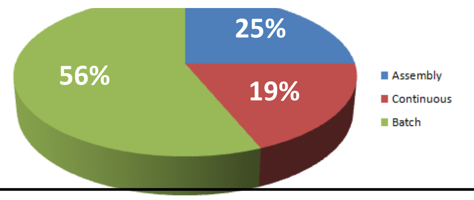
Sent questionnaires	162
Total responses	39
Final usable responses	32
Response rate as a percentage of sent questionnaires	20%

Descriptive statistics

Description	Less than 10	Less than 200	Bigger than 200
Employee number (size)	18.75% 6	25.00% 8	56.25% 18
Description	**Private sector**	**Public sector**	**Multi-national**
Type of ownership	62.50% 20	18.75% 6	18.75% 6
Description	**Batch**	**Continuous**	**Assembly**
production system	56.25% 18	18.75% 6	25.00% 8







Description	Chemical industries	electronic industries	Food industries
Industrial sector	40.63% 13	12.50% 4	9.38% 3
Description	**Metal industries**	**Engineer-ing industries**	**Textile industries**
Industrial sector	6.25% 2	25.00% 8	6.25% 2

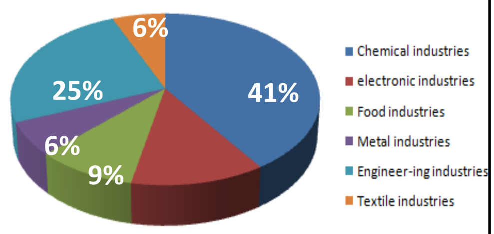


Figure (2) depicts total and percentage for each industrial sector, companies' size, production system, and type of ownership.

Observed variables test

Convergent Validity

Indicators Loading

Convergent validity is the extent to which a measure correlates positively with alternative measures of the same construct. To establish convergent validity, researchers consider the outer loadings of the indicators, as well as the average variance extracted (AVE) (Hair *et al.*, 2014, p.102).

Table (2) Indicators Loading, Composite Reliability and AVE Testing Results

Variable Name	Items	Loading	Composite Reliability	Average Variance Extracted (AVE)
Technical Factors	TF1	0.686	**0.903**	**0.579**
	TF2	0.459		
	TF3	0.731		
	TF4	0.841		
	TF5	0.796		
	TF6	0.834		
	TF7	0.897		
Social Factors	SF2	0.836	**0.920**	**0.697**
	SF3	0.873		
	SF4	0.738		
	SF5	0.848		
	SF6	0.870		
DL Readiness	RDY1	0.742	**0.942**	**0.731**
	RDY2	0.807		
	RDY3	0.752		
	RDY4	0.956		
	RDY5	0.891		
	RDY6	0.953		
Smart Manufacturing	SM1	0.533	**0.918**	**0.568**
	SM3	0.939		
	SM4	0.893		
	SM 5	0.796		
	SM 6	0.459		
	SM 7	0.480		
	SM 8	0.798		
	SM 9	0.788		
	SM 10	0.905		

Discriminant Validity

Cross Loadings

Discriminant validity expresses the extent to which a construct actually differs from other constructs by empirical standards (Hair *et al.*, 2014, p. 104), as there are two methods for analyzing Discriminant validity when evaluating reflective measurement models, namely the Fornell-larcker criterion and Cross Loadings. (Hair *et al.*, 2014, p. 100; Hair *et al.*, 2011, p. 146).

Table (3) Cross Loadings Testing Result

Items	Technical Factors	Social Factors	DL Readiness	Smart Manufacturing
TF1	0.686	0.625	0.440	0.121
TF2	0.459	0.431	0.232	0.106
TF3	0.731	0.564	0.587	0.472
TF4	0.841	0.793	0.639	0.474
TF5	0.796	0.472	0.747	0.715
TF6	0.834	0.284	0.581	0.636
TF7	0.897	0.447	0.586	0.489
SF2	0.610	0.836	0.733	0.670
SF3	0.451	0.873	0.450	0.128
SF4	0.392	0.738	0.689	0.432
SF5	0.665	0.848	0.493	0.156
SF6	0.671	0.870	0.503	0.219
RDY1	0.712	0.503	0.742	0.467
RDY2	0.672	0.637	0.807	0.761
RDY3	0.400	0.516	0.752	0.651
RDY4	0.626	0.774	0.956	0.786
RDY5	0.690	0.602	0.891	0.741
RDY6	0.698	0.698	0.953	0.794
SM1	0.439	0.124	0.406	0.533
SM3	0.708	0.501	0.832	0.939
SM4	0.570	0.552	0.788	0.893
SM 5	0.377	0.264	0.531	0.796
SM 6	0.356	-0.107	0.234	0.459
SM 7	0.184	0.372	0.321	0.480
SM 8	0.421	0.247	0.567	0.798
SM 9	0.488	0.402	0.764	0.788
SM 10	0.517	0.371	0.787	0.905

Examining the reliability values of each item, table (2) revealed that one of the items (SF1 with the "Social Factors" variable) and (RDY7 with "DL readiness" variable) did not achieve the required reliability value of 0.102, and 0.366 respectively as did the items (SM2 – SM11 – SM12) with the "smart manufacturing" variable. The required reliability values (0.194 - 0.102 - 0.279) were not met because the specified range of reliability for each item must be greater than or equal to 0.70 and less than 0.95.

i. The element that did not achieve the required reliability value was excluded, with the exclusion not exceeding the permissible limit of 20% of the total number of elements in the research model, (5 ÷ 32) * 100 = 15.6%.

ii. Table (2) displays the reliability values after re-analysis, excluding the elements that did not achieve the required value.

iii. By examining the reliability values of each item, we discover that the group of items (TF1 – TF2) (SM1- SM6 – SM7) did not achieve the required reliability values, and they were kept because they fall in the range of 0.40 to 0.70, and when excluded, they did not change the minimum values of composite reliability or average variance extracted for a variable.

iv. All components of the composite reliability for all variables are greater than 0.70, and all components of the average variance extracted (AVE) are greater than 0.50, indicating convergence of all elements of the research model and qualifying them for Discriminant validity analysis.

v. Examining the values in Table (3), we discover that the value of each element for each variable in the model is recorded as the largest value that falls within the range of this element in relation to all other variables in the model, indicating the differentiation and non-overlapping of each element of the model for each variable.

vi. Table (4) shows that the value at each variable's intersection with itself represents the largest value in its horizontal and vertical range (the largest value in relation to other variables). For example, the "social factors" variable has a value of 0.835, which is the highest value in the variable's horizontal range. (0.835 > 0.736), (0.862 > 0.457), and it is also the largest value in the variable's vertical range (0.835 > 0.670), and so on for the remaining values with the exception of "Smart manufacturing", which is represented by the shaded numbers.

Based on the results of the previous step, Heterotrait-Monotrait (HTMT) analysis was performed as an alternative criterion to ensure the Discriminant validity of each model variable, as Henseler *et al.* (2015) demonstrated that this criterion can be relied on as an alternative or another way to estimate the Discriminant validity of the research model, and the results of this analysis are presented in the table (5).

Table (4) Fornell-larcker criterion Testing Result

Variables	DL Readiness	Smart Manufacturing	Social Factors	Technical Factors
DL Readiness	**0.٨٥٥**			
Smart Manufacturing	**0.829**	**0.754**		
Social Factors	0.736	0.457	**0.835**	
Technical Factors	0.748	0.621	0.670	**0.761**

Table (5) Heterotrait-Monotrait criterion Testing Result

Variables	DL Readiness	Smart Manufacturing	Social Factors	Technical Factors
DL Readiness				
Smart Manufacturing	0.870			
Social Factors	0.760	0.443		
Technical Factors	0.796	0.652	0.733	

Table (5) clearly shows that all elements have a value less than 0.90, indicating that the Discriminant and correlation of each variable in the model. According to Henseler *et al.* (2015) lack of Discriminant validity emerges when the values of (HTMT) are higher than 0.90.

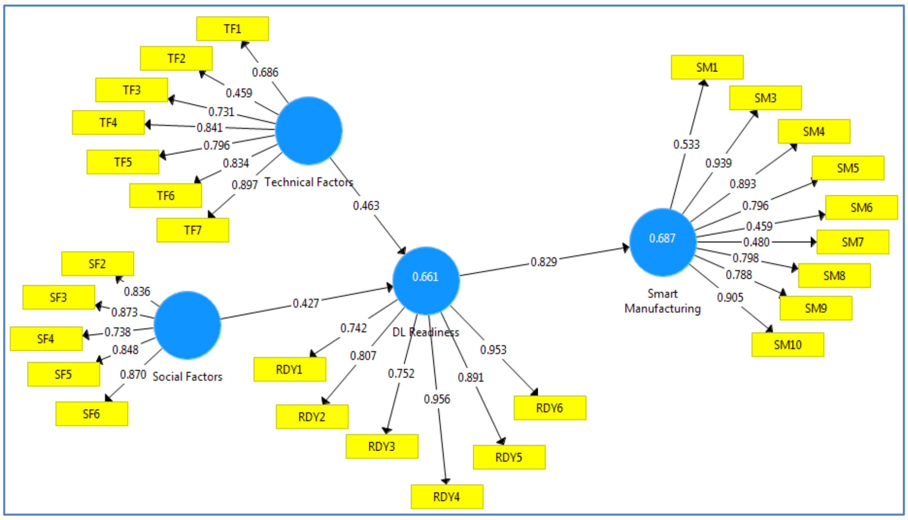


Figure (3): reliability of each indicator of the research model

Source: Smart-PLS output

Assessment of Structural Model (Testing hypotheses)

Testing hypotheses (H1, H2, and H3)

A significance level less than 0.01 and positive **β** values are reached, indicating a positive correlation, whether direct or indirect, between the research variables as shown in table (6).

Table (6) research variables significance

Research variables relationships	β Beta	STD. Error	T	sig.
Technical Factors → DL Readiness	**0.643**	**0.072**	**6.400**	**0.000**
Social Factors → DL Readiness	**0.427**	**0.067**	**6.409**	**0.000**
DL Readiness → Smart Manufacturing	**0.829**	**0.063**	**13.128**	**0.000**

Table (7) hypotheses testing results

Hypothesis	*p*-value	Supported / not supported
H1: Technical Factors → DL Readiness	**< 0.01**	**Supported**
H2: Social Factors → DL Readiness	**< 0.01**	**Supported**
H3: DL Readiness → Smart Manufacturing	**< 0.01**	**Supported**

Since all research hypotheses are supported by significance levels of 0.01, the effect size for both independent and dependent variables can be determined as shown in tables (8) and (9).

Table (8) Size Effect on DL Readiness and Smart Manufacturing

Variable	R^2	Result
DL Readiness	**0.661**	Moderate
Smart Manufacturing	**0.687**	High

According to table (8), social and technical factors are responsible for around 66% of the change in organization's readiness to employ DL techniques in the Egyptian context. Furthermore, DL readiness is responsible for around 69% of the change Smart Manufacturing technologies application in Egyptian industrial companies.

The R^2 coefficient is used to identify the effect size for each variable separately to describe the relationship between social factors and technical factors in general, F^2 coefficient should be used to determine the effect size for each variable individually to describe the relationship through each variable separately as shown in table (9):

Table (9) Size Effect of Technical and Social Factors on DL readiness

Variable	F^2	Result
Technical Factors → DL Readiness	**0.348**	Medium
Social Factors → DL Readiness	**0.296**	Medium

social and technical factors have a moderate effect on DL readiness, while the effect size of DL readiness on Smart Manufacturing are high, according to Chin (1998) the value of R^2 that above 0.67 considered high, while values ranging from 0.33 to 0.67 are moderate whereas values between 0.19 and 0.33 are weak and any R^2 values less than 0.19 are unacceptable. The values of F^2 above 0.35 considered large effect size while values ranging from 0.15 to 0.35 are medium effect size, whereas values between 0.02 to 0.15 considered small effects, finally F^2 values less than 0.02 are considering with no affect size.

Testing Hypotheses (H4- H5)

As shown in Table (10), "necessary knowledge about DL technique", were the elements that most express the extent of the organization's readiness towards applying DL technique (average 3.8438), followed in second place by "support from top management to judge and work on DL technique" (average 3.8125). On the other hand, the least element expressing readiness was "we experience a pressure to work DL technique" with an average of 2.9688.

Table (10) Extent of DL Readiness

Organization's DL readiness Items	Mean	STDEV	STD Error
We experience a pressure to work DL technique.	2.9688	0.24381	1.37921
We have the willingness to take risks to experiment on DL technique.	3.7188	0.19692	1.11397
We have the necessary knowledge about DL technique.	3.8438	0.14966	0.84660
We have necessary support from top management to judge and work on DL technique.	3.8125	0.21269	1.20315
Our employees have the right competencies to work on DL technique.	3.7813	0.16640	0.94132
Our employees have the right motivation to judge and work on DL technique.	3.4375	0.19017	1.07576
We have economic freedom to on DL technique.	3.7813	0.14009	0.79248

Table (11) Extent of Smart Manufacturing Application

Smart Manufacturing Items	Mean	STDEV	STD Error
Big data and business analytics.	4.1250	0.16033	0.90696
Autonomous robots.	3.0938	0.17577	0.99545
Simulation.	3.0938	0.19239	1.08834
Horizontal and vertical system integration.	3.5313	0.15544	0.87931
Industrial Internet of Things (IoT) (including sensors).	3.3438	0.20384	1.15310
Cyber security.	3.5938	0.19499	1.10306
Additive manufacturing (such as 3D printing).	3.7188	0.18640	1.05446
Augmented reality.	4.3438	0.10634	0.60158
Cloud Computing.	3.5625	0.21031	1.18967
Mobile technologies (tablets, mobile phones, GPS devices, laptops).	3.2500	0.18513	1.04727
Artificial Intelligence.	3.1563	0.19628	1.11034
Radio Frequency Identification (RFID) and real-time positioning system (RTLS) technologies.	3.0625	0.18479	1.04534

Table (12) Technical Factors Applied

Technical Factors Items	Mean	STDEV	STD Error
Panels in production processes and displays for work activities	4.3077	0.92206	0.14765
Detailed descriptions of workplace accommodation and adjustment of equipment and storage of semi finished products	4.2308	0.58316	0.09338
Binding process flow to optimize the changeover	4.3846	0.63610	0.10138
Methods for ensuring the quality of production	4.5385	0.50504	0.08087
Methods of operations management using mathematical analysis of production (e.g.: 6 Sigma)	3.8462	0.96077	0.15385
Methods for continuous improvement of production processes (e.g.: CIP, kaizen, quality circles)	3.8462	1.11304	0.17823
Methods for improving internal logistics	4.3846	0.49286	0.07892

According to Table (11), "augmented reality" and "big data and business analytics" were the most commonly used (averages of 4.3438 and 4.1250, respectively), while "additive manufacturing technology (such as 3D printing)" came in second with an average of 3.7188. "Cyber security" came in third (average 3.5938), while "Cloud Computing" and "Horizontal and vertical system integration" came in fourth and fifth (averages 3.5625 and 3.5313).

Radio Frequency Identification (RFID) and real-time positioning system (RTLS) technologies (average 3.0625) simulation as well as Autonomous robots (average 3.0938) were the least applied technologies, followed by Mobile technologies (tablets, mobile phones, GPS devices, laptops) with an average of 3.2500, and finally Industrial Internet of Things (IoT) with an average of 3.3438.

Table (12) demonstrates the significance of "Methods for ensuring production quality" in terms of technical factors applied to DL techniques in the organizations under study, as they appear at the top of the scale, followed by "Binding process flow to optimize the changeover" and "Methods for improving internal logistics" while "Methods for continuous improvement of production processes" and "Methods of operations management using mathematical analysis of production" are at the bottom of the scale.

Table (13) Social Factors Applied

Social Factors Items	Mean	STDEV	STD Error
IT-based self-learning programs (e-learning)	3.7692	0.90209	0.14445
Standardized methods of job design to improve health or safety	4.0000	0.88852	0.14228
Tools to promote employee engagement (e.g.: free canteen, childcare)	4.0000	0.97333	0.15586
Tools for retaining older employees or their knowledge in the company (e.g.: composition of teams with a focus on age diversity)	3.3846	1.01607	0.16270
Training opportunities with an interdisciplinary focus	4.3077	0.73104	0.11706
Training and development of employees’ skills geared towards creativity and innovation	4.2308	0.80986	0.12968

Table (13) demonstrates the importance of training among the social factors related to the application of DL techniques in the organizations under study, with "Training opportunities with an interdisciplinary focus" appearing at the top of the scale, followed by "Training and development of employees' skills geared towards creativity and innovation" while "Tools for retaining older employees or their knowledge in the company" appearing at the bottom.

Discussion and Conclusion

The findings demonstrated a positive relationship between organization's readiness to deploy DL techniques and the extent to which they applied smart manufacturing technologies in the Egyptian context. In other words, in the Egyptian environment clearly explained that the readiness of organizations to implement DL techniques was responsible for approximately 66% of the change in the adoption of these organization's application of smart manufacturing technologies in the Egyptian environment.

This research additionally examines how social and technical factors affect an organization's readiness to implement DL techniques from a Socio-technical perspective, where the results indicated a positive relationship between social factors and technical factors in terms of Egyptian industrial organization's readiness to implement DL techniques, and that improving the social aspects of the manufacturing system has a positive impact on the organization's readiness to implement DL techniques in the Egyptian environment, as well as improving the technical aspects of manufacturing operations has a positive impact on the organization's readiness to implement DL techniques in the Egyptian environment.

These findings confirm the study's hypotheses (*H1*, *H2*, and *H3*), as well as the conclusions of (Alsheibani *et al.*, 2018; Wang *et al.,* 2018); Stentoft *et al.,* 2021; Issa *et al.,* 2022) from AI adoption perspective with considering that the current study emphasize on DL as AI technique, on the other hand from social and technical perspective, this findings consistent with (Marcon *et al.*, 2021; Smit *et al.*, 2023). Nonetheless, the factors influence according to this study is moderate based on the results.

According to the research findings, Egyptian industrial organizations have a "medium level of readiness," which means they are partially ready to apply DL techniques, and that this medium readiness, or what we might call partial readiness, was driven by necessary knowledge about DL techniques. This could be due to the new reality that most organizations are experiencing, not only in Egypt but globally, as a result of the integration of artificial intelligence technologies into all aspects of business, particularly manufacturing operations, as a reflection of the new reality imposed by these technologies, which would push the industrial community to work in accordance with the data of this environment. This is supported by "management to judge and work on DL techniques", and "employees have the appropriate competencies to work with DL techniques," as those elements ranked right after them in the research findings.

Furthermore, the results confirm that the average value of the DL readiness variable is higher out of 3, which partially contradicts the hypothesis (*H4*), which claims that "*Egyptian industrial organizations achieve a low degree of readiness towards applying DL techniques*" as Egyptian industrial organizations demonstrated a "medium level of readiness." All statements are roughly between the average of 3 and below 4, with the exception of one that nearly touches the average of 3.

However, when it comes to the application processes of smart manufacturing technologies, the research found that Egyptian manufacturers are still using production technologies that are somewhat distant from artificial intelligence technologies, although augmented reality being the technology most used by Egyptian businesses, followed by "business analytics" Next, "Additive manufacturing" such as 3D printing. However, the technologies directly related to artificial intelligence, such as (autonomous robots, Internet of Things (IoT), and simulation), which appeared in recent years, were considered the least applied by Egyptian industrial business organizations, indicating that they are still controlled by technologies that do not directly rely on artificial intelligence. These findings corroborate hypothesis (*H5*), which claims that "*the most advanced smart manufacturing technologies are applied to a low degree by Egyptian industrial organization*".

Finally, the research results show that the private sector has the highest representation of the research sample, surpassing public sector companies and multinational corporations, which may be due to the state's privatization policies and the limitation of the public sector's role in production operations in a large way, as the production system was batch-based. The biggest percentage of continuous and assembly production systems were used, while small companies were used to represent the research sample in terms of the number of workers, but large companies topped the sample representation, followed by medium-sized companies.

In summary, the previously discussed indicates that in order for Egyptian industrial business organizations to advance to the point where they are applying artificial intelligence technologies—including DL techniques—they must improve social and technical factors that impact their readiness. This will allow them to apply these technologies at a level that will enhance smart manufacturing.

Managerial Implications

Previous research indicates that the following managerial adjustments ought to be made by Egyptian decision-makers, managers, producers, and government representatives:

Given that industrial organizations currently have an average level of readiness, the Egyptian government must support these organizations more in order to increase their readiness to implement DL techniques. This support should take the form of financial incentives and careful attention to training programs, particularly in light of the research findings that highlight the significance of training within the social factors applied to the manufacturing system in Egyptian industrial organizations.

The research findings indicate that technical factors play a significant role in an organization's readiness to adopt artificial intelligence technologies and their relationship. Therefore, industrial companies should make greater investments in the technical sector by enhancing their social and technical environments, as this will improve their capacity to get ready for the use of DL technologies. Consequently, the optimal deployment of smart manufacturing technologies.

Since artificial intelligence is controlling the environment in which modern manufacturing trends are being produced, Egyptian manufacturers would be well-advised to integrate artificial intelligence techniques—particularly DL techniques—with manufacturing operations. This is especially true given that research indicates Egyptian industrial organizations possess the necessary competencies to operate in this field.

Research Limitation and Future Directions

Since this study represents the first attempt to examine Egyptian industrial organization's readiness to use DL techniques as a essential artificial intelligence technology, we must increase our knowledge of the variables influencing these variables' capacity to be implemented, these variables can be studied in greater detail by Examining organizational and environmental factors; that is, consider studying these factors from a sustainability perspective by including environmental factors in addition to social and technical factors.

Similar studies can also be carried out in other developing nations, allowing us to compare the readiness of industrial organizations in those nations to deploy these technologies in various circumstances and identify similarities and differences.

Due to the survey's small sample size, similar research on a bigger sample is required to support the generalization of research findings to a larger population. Furthermore, an extensive survey combined with a thorough case study would be the perfect approach for AI especially in deep learning research. Moreover, different modeling approaches could be employed as an analysis tool to provide greater richness and a deeper knowledge of the current issue.

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الاستعداد للتعلم العميق للتصنيع الذكي: منهج اجتماعي-تقني

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المستخلص

هدفت الدراسة إلى التعرف على الوضع الحالي لاستعداد المنظمات الصناعية المصرية لاستخدام تقنيات التعلم العميق، وكذلك التعرف على العوامل الفنية والاجتماعية التي تؤثر على استعدادها لاستخدام تقنيات الذكاء الاصطناعي المتقدمة. استخدمت الدراسة الاستبيان كأداة لجمع بيانات من ١٦٢ مصنعًا في مختلف القطاعات الصناعية في مصر. واعتمد اختبار الفروض على أسلوب نمذجة المعادلة البنائية، والذي يستخدم أسلوب المربعات الصغرى الجزئية القائم على التباين لتحليل البيانات من خلال برنامج "Smart-PLS". وقد تم اختيار هذه الطريقة لأنها الأكثر ملائمة لخصائص الدراسة، مع الأخذ في الاعتبار عوامل مثل حجم العينة ونوع البيانات. وأظهرت النتائج أن تعزيز الجوانب الفنية والاجتماعية لنظام التصنيع له تأثير إيجابي على استعداد المنظمات لتطبيق تقنيات التعلم العميق في البيئة المصرية، والذي بدوره له تأثير على قدرة هذه المنظمات على تطبيق تقنيات التصنيع الذكي. بالإضافة إلى ذلك، توصلت الدراسة إلى أن المصنعين المصريين جاهزون جزئيًا لاستخدام تقنيات التعلم العميق، بما يمثل مستوى استعداد متوسط، وأنهم لايزالون يستخدمون أنظمة تصنيع بعيدة إلى حد ما عن تكنولوجيا الذكاء الاصطناعي. تقدم الدراسة مجموعة من التوجيهات لتحسين استعداد المنظمة للتعلم العميق للتصنيع الذكي في القطاع الصناعي المصري.

الكلمات المفتاحية: التعلم العميق؛ التصنيع الذكي؛ النظرية الاجتماعية التقنية؛ الاستعداد للتعلم العميق؛ المنظمات الصناعية المصرية.