# A FRAMEWORK FOR SMART DAIRY INDUSTRY: TECHNOLOGICAL & ORGANISATIONAL ASPECT

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## **ABSTRACT**

The research demonstrates the development of a framework for improvement in the dairy industry using technological and organizational domains concerning Industry 4.0. The technological domain includes smart factories, smart operations, smart products, and data-driven services. On the other hand, the organizational domain includes two factors: employees and cyber security. The proposed framework will benefit the establishment of a new Dairy industry concerning Industry 4.0. Structural equation modeling (SEM) has been applied to all six latent factors namely smart factory, smart operations, smart product, data-driven services, employees, and cyber security to evaluate the interrelationship of factors. In the research work, Exploratory factor analysis (EFA) was carried out using the Principal Component Analysis (PCA) to interpret the constructs before taking up Confirmatory factor analysis (CFA). Then, using AMOS software, all the latent variables were examined to determine how well the indices fit the theory. In the end, the approach produced structural equation modeling (SEM), which goodness of fit statistics was used to assess.

**Keywords:** Industry 4.0, Smart Dairy Industry Framework, Structural Equation Modeling (SEM), Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA).



#### 1. INTRODUCTION

In the dairy industry, Industry 4.0 can bring technological revolution allowing the integration of systems with subsystems and, the incorporation of data-driven technologies. The inclusion of Radio-frequency identification (RFID), cloud computing, the Internet of Things (IoT), smart sensors, artificial intelligence (AI), etc. can automate the entire industrial ecosystem. The inclusion of these technological domains can benefit production flexibility, efficiency, and productivity in the dairy industry. This will make businesses smarter with a high level of automation resulting revolution in the dairy industry, thereby making all sectors start, i.e., smart factory, smart operations, smart product, and smart delivery. This proposed framework includes two major domains namely organizational and technological aspects. The technological domain consists of Smart Factories, Smart Operations, Data-Driven Services, and human System Integration, whereas the organizational domain consists of employee and cyber security aspects. The framework for the smart dairy industry in the Indian subcontinent is designed on industry 4.0 design principles

#### 2. LITERATURE REVIEW

**Hermann et. al., (2015)** reported that despite the lack of a widely recognized definition, Industry 4.0 is presently a major focus for many businesses, research facilities, and academic institutions. This makes both implementing industry 4.0 scenarios and having scholarly discussions on the issue challenging. Six design concepts have been identified: virtualization, decentralization, interoperability, service orientation, and modularity. These are necessary for its execution. The scientific and practitioner communities are talking about Industry 4.0. The article defined Industry 4.0 and then divided its practical contributions into two categories: First, the definition provided for Industry 4.0 aids in elucidating practitioners' basic grasp of the phrase. Secondly, Industry 4.0 scenarios may be implemented in businesses using the six design principles. They provide direction throughout installation and assist in identifying possible use cases.

**Hermann et al. (2016)** Note that smart items will be able to recall their manufacturing history and current status within the smart factory. Through the provision of instructions to machines, the intelligent goods will be able to actively navigate their way through the manufacturing process to complete necessary tasks. A move away from the centrally managed factories of today will result in a decentralized control of the manufacturing process. According to the authors, a key component of Industry 4.0 is information openness, and they emphasize the need for real-time distribution of process-critical data. Data that allows for the early identification of anomalies and deviations that might have an impact on the production's outcome is an example of process-critical data.

**Stock and Seliger (2016)** revealed that autonomously operated transport equipment, including Automated Guiding Vehicles, will distinguish the in-house transportation (AGV). All materials in the production must be traceable at all times, meaning they must be able to be quickly identified and localized, to facilitate the automated transportation of equipment. All materials, whether on a carrier or kept at the line side, ought to be traceable. For this, a variety of technologies are available; two examples are Quick Response (QR) codes and Radio Frequency Identification (RFID) tags.

**McKinsey, (2016)** has looked into the various Industry 4.0 applications that American and German corporations have deemed important. Real-time supply chain optimization, predictive maintenance, remote monitoring and control, and digital performance management, and digital quality management are the top five applications. Additionally, the research looked at which applications the firms had advanced, concluding that advancements had been achieved in the following areas: predictive maintenance, smart energy usage, Remote control, digital performance management, and investigation, and digital quality management.

**Chen (2017)** stated that the integration and intricate interdependencies between cyberspace and the actual world are the primary goals of the new generation of digital systems known as Cyber-Physical Systems (CPS). Compute, communication, control, and physical attributes are all intimately interwoven to form a CPS. Currently, academics, business, and government are interested in CPS.

**Lu Y (2017)** submitted In recent literature, there has been a lot of discussion about Germany was the birthplace of Industry 4.0, the fourth industrial revolution. It is closely related to enterprise architecture (EA), cyber-physical systems (CPS), Internet of Things (IoT), Enterprise Integration (EI), and information and communications technology (ICT).

Thirupathi and Vinodh (2016) outlined the use of SEM and interpretative structural modeling (ISM) for the examination of legitimate manufacturing parameters in the Indian automobile integrant industry. In today's world, for getting a competitive advantage sustainable production is very important. Various factors enable sustainable production such as social cohesion, environmental sustainability, and economic prosperity and the relation between these factors needs to be analyzed. Interpretive structural modeling has been used for developing the theoretical model and measurement models and structural equation modeling are used for verifying these models. They have presented an integrated SEM and ISM to construct the models for the automotive component manufacturing sector. From the results, they have found out that ISM is a very powerful technique for establishing the structural relationship between the various factors of sustainability.

Lee, J. and Bagheri, B. and Kao, H. (2015) These days, frequent troubleshooting scenarios reduce or even cease work and demotivate staff members. Finally, it should be noted that the existing state of the industry is inflexible and difficult to alter; innovations are rare and expensive, and price reductions for raw materials typically result in worse quality and higher process costs, which in turn causes profit margins to continuously erode. Additionally, improvisation increases, and development timeframes lengthen when there is a decline in the internal knowledge base. Production systems lack a self-aware core that could learn and operate without continual human supervision, despite their high

level of automation. All of these inconveniences highlight the necessity for the next, much-needed industrial manufacturing revolution, or "industry 4.0," which will bring about several improved features over current production processes.

**Reiner, A. (2014)** Industry 4.0 intends the implementation of interconnected, smart, and self-controlled structures and systems.

**Kagermann, H.; Wahlster, W.; Held, J.** (2014) Consequently, smart operations are made possible by procedures constructed with Industry 4.0 technology, which offer creative, value-added, adaptable, dependable, and efficient processes. Technology advancements therefore present new business prospects as well as new company strategies.

#### 3. RESEARCH METHODOLOGY

This research follows exploratory and descriptive research. Exploratory research is used while quite few information is available about the expected outcome and variables have intrinsic relationships among them. The exploratory research can be used founded on rather basic methodologies like case studies and descriptive statistical techniques such as Exploratory Factor Analysis (EFA). This makes it feasible to identify potential connections and patterns and further scope of detailed, rigorous analysis and models.

The method of description is applied following establishment of a relationship among the latent variables mentioned in Table 1 namely Smart factory, smart operations, smart products, data-driven services, employees, and cyber security, and the relationship has been developed using exploratory research. The survey data and its preliminary exploratory study were utilized to inform the construction of the conceptual framework model, which was then developed using the descriptive technique. The survey design and implementation were based on the findings of the previous literature review.

Lastly, In conclusion, the study report employed an explanatory approach by explaining and expanding on the application of Industry 4.0 to the dairy industry in the Indian context, with a particular emphasis on the thorough analysis and justification of the enhancement of the dairy industry through the use of the smart dairy industry framework.

**Method of Primary Data Collection:** Primary data was gathered both offline and online using a ten-item, closed-ended, structured questionnaire between December 20, 2021, and March 25, 2022.

**Number of samples:** Ten dairy plant people from Punjab, Chandigarh, and the Delhi NCR region made up the sample size.

**Sample unit:** The sample units were engineers, HR Personnel, and workers in 10 Dairy plants.

Sample Technique: Simple random sampling.

**Methodology of Analysis:** SEM is utilized to ascertain the structural relationship among the variables that are being investigated which leads to the latent variables mentioned in Table 1, namely Smart factory, smart operations, smart products, and data-driven services, employees, and cyber security, to evaluate the inter-relationship of the latent variables.

## 4. TECHNOLOGICAL FACETS OF THE DAIRY INDUSTRY

## 4.1. SMART FACTORY

Industry 4.0, which promotes minimum human intervention in manufacturing and logistical systems with autonomous directing, regulating, and monitoring, has a very well-conceived idea of the "smart factor." The notion of the "smart factory" led to the development of the Cyber-Physical System (CPS), which combines connection, conversion, cyber, cognition, and configuration. The industrial sector—which includes milk plants—needs to focus more on integrating Industry 4.0 technologies, such as augmented reality, cyber-physical systems, and the Internet of Things. Intelligent control, self-growing knowledge base, perception, intelligent analysis, intelligent control, and decision-making are all features of the Cyber-Physical System (CPS), which combines cyber and physical systems.

### 4.2. SMART OPERATIONS AND MAINTENANCE

Industry 4.0's smart operations have undoubtedly brought about a digital revolution in the creation of innovative supply chain management. Industry 4.0's smart operations created new avenues for digital transformation that led to the creation of completely novel supply chain management. It's interesting to note that self-maintenance systems—which include data collection systems, various smart sensors, wireless sensor networks, adaptive systems, end-user systems, and processes are necessary for smart operations. (Figure 1)

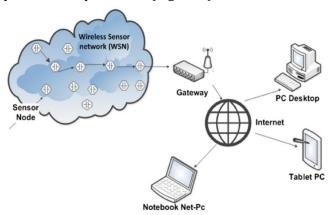


Figure 1 Wireless sensor network (WSN) Source: Sarbjeet et al., 2014

The self-maintenance execution uses historical data and performs real-time, fast, and accurate data acquisition and processing, (Figure 2) for decision support for better maintenance systems (Sarbjeet et. al., 2014).

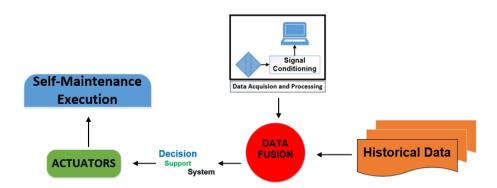


Figure 2 Architecture of Self-maintenance system (Source: Modified from Sarbjeet et al., 2014)

#### 4.3. SMART PRODUCTS

With the use of components of information, communication, and technology (ICT) including bar codes, interfaces, sensors, RFID tags, etc., the smart product has the capability of real-time monitoring of manufacturing processes. Improved communication between producers and customers is facilitated by this usage of ICT.

#### 4.4. DATA-DRIVEN SERVICES

The sector has to provide better data-driven services to help customers make decisions by providing them with analytics and data that provide value for them, as was indicated in smart factories and smart operations (Schüritz, Farrell, Wixom, & Satzger, 2019). This area is significant from the standpoint of the milk business because it encourages the

requirement that physical goods supplied have sensors installed for them to transmit, receive, and analyze the required data.

#### 4.5. HUMAN SYSTEM INTEGRATION

Aspects of system integration include increased system safety, greater control over life cycle costs, and user-centric design for better human-machine systems. Furthermore, Human needs are integrated into systems as part of human system integration (HSI) and aspects of system design.

### 5. ORGANIZATIONAL ASPECTS OF THE DAIRY INDUSTRY

Strategy and organization in Industry 4.0 is a very important theme for the overall improvement of any Industry including dairy. This not only helps in the improvement of processes and products but also promotes the growth of entirely new business models (Lichtblau et al. 2015). Without question, the dairy industries require significant organizational and strategic reforms at every level of the company. In the realm of strategy and organization, there exist three distinct levels: corporate, business, and functional. From the top corporate level to the lowest functional level, the business sector can establish goals at every level of strategy. To have a better strategy in an organization, the degree of strategy should be at an optimum level with continuous improvement and development in strategic process and integration with industry. To be precise, the degree of strategy should be defined from the level of conception of organizational improvement and should be implemented enterprise-wide. Every dairy-related organization must have defined indicators for evaluating the performance and status of the organization/industry or implementation of Industry 4.0. The dairy industry needs to have an integrated system of indicators, which should be in sync with strategic processes.

No industrial sector survives without investment. In the initial phase, the industry can have investment in one area followed by investing in multiple domains. Industry 4.0 encompasses more than just leveraging technology to enhance business operations and output. It promotes the creation of unique business models (Lichtblau et al. 2015). It is pertinent to mention that, if any industry has to expand with good economic growth, there should be innovation management at its core. There needs to be uniform, interdepartmental innovation management. Innovation management involves the process of managing industrial innovation procedures from the beginning till its successful implementation. It deals with all activities and practices of designing and implementing an innovation strategy. Innovation management has four distinct steps:

- Generating Brainstorming sessions
- Capturing Idea sharing
- Evaluating Discussion on innovative ideas
- Prioritizing Prioritizing innovative ideas for implementation.

#### 5.1. EMPLOYEES

By evaluating staff competencies and contrasting their approaches to gaining new training and credentials, one may ascertain the maturity level in this area.

#### 5.2. CYBER SECURITY

Cyberattacks and operational risk have been noted to affect all enterprises in the past. Strategies for addressing the problem of cyber security need to be alert, and safe, and incorporate an information technology plan from the initial state.

#### 6. STRUCTURAL EQUATION MODELLING (SEM)

In this research paper, we have used, SEM to investigate the structural connection among the variables that are being investigated which leads to the latent variables mentioned in Table 1, namely Smart factory, smart operations, smart products, data-driven services, employees, and cyber security. This method combines multiple regression analysis

with factor analysis. In the research work, Exploratory factor analysis (EFA) was carried out using the principal component Analysis (PCA) to interpret the constructs before taking up Confirmatory factor analysis (CFA). Every single latent variable was then analyzed to determine the fit of the indices supported by the theory using AMOS software. The work finally led to SEM which was assessed using statistics for goodness of fit. The homogeneity of data was checked by carrying out the KMO test and Barlett's test (BT) for sample adequacy (Hair et al. 2006).

6.1. EXPLORATORY FACTOR ANALYSIS (EFA)

Latent Variables	Dimension Code	Sub-factors	Factors Code	
Smart Factory	SF	Current Equipment Infrastructure	CEI	
		Target Equipment Infrastructure	TEI	
		Digital Modelling	DM	
		Data Collection	DC	
		Data Usage	DU	
		IT Systems	IT	
Smart Operations	SO	System-integrated information sharing	SIIS	
		Autonomous work	AGW	
		Self-reacting processes	SRP	
		IT Security	ITS	
		Cloud Usage	CU	
Smart Products &	SPDDS	ICT add-on functionalities	ICT	
Data-Driven Services		Use of data	UD	
		Share of revenues	SR	
		Level of Data Usage	LDU	
Employees	EM	Employee Skills	ES	
		Employee Training	ET	
		Employee Education	EE	
Cyber Security	CS	Cyber Security management practices	CSRMP	
		Risk Mitigation	RM	
		Risk Assessment	RA	

**Table 1** List of Factors and Sub factors

The experimental findings of the KMO and BT test are in the desired range. Thereafter initial eigenvalues, the rotation sum of square loadings, and the extraction sums of squared loadings were computed on data consisting of 05 factors as listed in Table 1. The total variance calculated comes out to be 90.183 with more than one eigenvalue. In the present research, the 05 factors were (1) Smart Factory, (2) Smart operations, (3) Smart Products & and Data Driven Services clogging in the casing, (4) employee, and (5) cyber security.

Dimension Code	nension Code Skewness Kurtos		Kurtosis		Factor Loading	Cronbach's α	кмо
	Statistic	Std. Error	Statistic	Std. Error			
SF	0.267 0.283 -0.883 0.559 0.778 0.745		0.745	0.729			
	0.073	0.283	-0.676	0.559	0.564		
	0.333	0.283	-0.633	0.559	0.870		
	-0.099	0.283	-1.014	0.559	0.310		

100	0.706
SO       .062       0.283      860       0.559       0.796       0.743         .029       0.283      765       0.559       0.616         0.308       0.283      740       0.559       0.756         0.240       0.283       -0.731       0.559       0.590         0.079       0.283       -0.962       0.559       0.485         SP        073       0.283       -1.133       0.559       0.624       0.709         0.370       0.283       -0.657       0.559       0.685       0.642         DDS         0.161       0.283       -0.644       0.559       0.806       0.642        013       0.283      905       0.559       0.745         0.125       0.283       -1.018       0.559       0.658       0.627	0.706
DDS	0.706
0.308       0.283      740       0.559       0.756         0.240       0.283       -0.731       0.559       0.590         0.079       0.283       -0.962       0.559       0.485         SP      073       0.283       -1.133       0.559       0.624       0.709         0.370       0.283       -0.657       0.559       0.685         DDS       0.161       0.283       -0.644       0.559       0.806       0.642        013       0.283      905       0.559       0.745         0.125       0.283       -1.018       0.559       0.658       0.627	0.706
0.240       0.283       -0.731       0.559       0.590         0.079       0.283       -0.962       0.559       0.485         SP      073       0.283       -1.133       0.559       0.624       0.709         0.370       0.283       -0.657       0.559       0.685         DDS       0.161       0.283       -0.644       0.559       0.806       0.642        013       0.283      905       0.559       0.745         0.125       0.283       -1.018       0.559       0.765         EM       0.375       0.283       -0.834       0.559       0.658       0.627	
SP      073       0.283       -0.962       0.559       0.485         DDS       0.161       0.283       -0.657       0.559       0.685        013       0.283       -0.644       0.559       0.806       0.642        013       0.283      905       0.559       0.745         0.125       0.283       -1.018       0.559       0765         EM       0.375       0.283       -0.834       0.559       0.658       0.627	
SP      073       0.283       -1.133       0.559       0.624       0.709         0.370       0.283       -0.657       0.559       0.685         DDS       0.161       0.283       -0.644       0.559       0.806       0.642        013       0.283      905       0.559       0.745         0.125       0.283       -1.018       0.559       0765         EM       0.375       0.283       -0.834       0.559       0.658       0.627	
DDS     0.370     0.283     -0.657     0.559     0.685       -0.161     0.283     -0.644     0.559     0.806     0.642      013     0.283    905     0.559     0.745       0.125     0.283     -1.018     0.559     0765       EM     0.375     0.283     -0.834     0.559     0.658     0.627	
DDS     0.161     0.283     -0.644     0.559     0.806     0.642      013     0.283    905     0.559     0.745       0.125     0.283     -1.018     0.559     0765       EM     0.375     0.283     -0.834     0.559     0.658     0.627	0.700
013     0.283    905     0.559     0.745       0.125     0.283     -1.018     0.559     0765       EM     0.375     0.283     -0.834     0.559     0.658     0.627	
0.125     0.283     -1.018     0.559     0765       EM     0.375     0.283     -0.834     0.559     0.658     0.627	0.780
<b>EM</b> 0.375 0.283 -0.834 0.559 0.658 0.627	
0.088 0.283 -0.657 0.559 0.617	0.773
0.772 0.283 1.247 0.559 0.772	
<b>CS</b> 026 0.283 -0.794 0.559 0.887 0.770	0.765
013 0.283 -0.483 0.559 0.896	

**Table 2** Factors and its scale reliabilities

Cronbach's Alpha was employed to evaluate the legality of the information and it has been observed that results obtained for Cronbach's Alpha of almost all the factors are within acceptable limits which are equal to or greater than 0.7 (Kannan & Tan, 2005). The Cronbach's Alpha was obtained after carrying out a reliability analysis on SPSS. Kaiser-Meyer-Olkin (KMO) test to ensure that the sample is adequate. The higher values of KMO signify a better correlation between the pair of variables. The KMO values should be higher than 0.60 as per the literature (Kaiser, 1974). But if KMO values lie within 0.80 and 0.90, It indicates that factor analysis was best served by the inter-correlation matrix (Reise et al., 2000). All of the factors have KMO values that are more than 0.6, making them perfect for factor analysis (Pett et al., 2003).

**Table 3** Component Scores and Loadings

Total Variar	nce Explained								
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.211	10.052	10.052	2.211	10.052	10.052	1.758	7.992	7.992
2	1.987	9.032	19.084	1.987	9.032	19.084	1.628	7.402	15.394
3	1.71	7.772	26.856	1.71	7.772	26.856	1.578	7.173	22.567
4	1.624	7.384	34.239	1.624	7.384	34.239	1.566	7.119	29.686
5	1.482	6.736	40.976	1.482	6.736	40.976	1.542	7.01	36.696
6	1.368	6.218	47.193	1.368	6.218	47.193	1.533	6.97	43.665
7	1.331	6.052	53.246	1.331	6.052	53.246	1.519	6.906	50.572
8	1.163	5.285	58.53	1.163	5.285	58.53	1.449	6.586	57.158

9	1.095	4.977	63.507	1.095	4.977	63.507	1.397	6.349	63.507
10	0.972	4.418	67.925						
11	0.943	4.287	72.213						
12	0.863	3.922	76.135						
13	0.819	3.723	79.858						
14	0.695	3.161	83.019						
15	0.675	3.066	86.085						
16	0.612	2.784	88.869						
17	0.543	2.468	91.337						
18	0.509	2.315	93.652						
19	0.493	2.242	95.894						
20	0.34	1.546	97.44						
21	0.305	1.387	98.827						
22	0.258	1.173	100						
Extracti	i <b>on Method</b> Princ	cipal Componer	nt Analysis.				'		

## 6.2. CONFIRMATORY FACTOR ANALYSIS

The (1) Smart Factory, (2) Smart operations, (3) Smart Products & and Data Driven Services (4) employee, and (5) cyber security factors were reiterated by the confirmatory factor analysis (CFA). There are two degrees of analysis; measurement model and structural model First of all, all the factors and their sub-factors are analysed as they have to be integrated at the end to develop the best-fitted model. Figure 3, shows the 1-factor congeneric model for all factors. The rectangle represents the evaluated variables and the circle represents the unobserved or latent variables (Anderson & Gerbing, 1988).

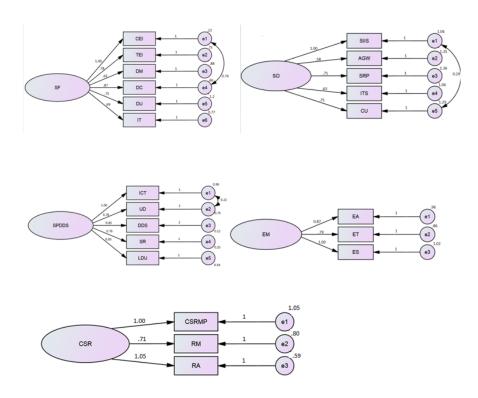


Figure 3 One factor congeneric model for all factors

#### 6.2.1. FIRST-ORDER CONFIRMATORY FACTOR ANALYSIS

After validating all the parameters individually, the first-order confirmatory factor analysis was carried out using all these factors, and then the latent variable model was analyzed. Table 4 shows the results of the structural model and suggested values for the satisfactory model fit. From the table, it is clear that all the goodness of fit statistics were within the recommended boundaries and hence there was no need to delete any sub-factors in confirmatory factor analysis as every element has statistical significance. Hence, both the models i.e. the data are adequately fitted by the structural model and measurement model. The summary and results of confirmatory factor analysis Table 4. Squared multiple correlations (R2), maximum shared variance (MSV), average variance extracted (AVE), composite reliability (CR), and average shared variance (ASV) are shown in Table 4. Based on the review of the literature, it has been found that the criteria were validated if the value of CR≥0.6. From Table 4, the value of squared multiple correlations (R2) was found to be higher ranging between 0.216 and 0.90 that implies all the factors were a good fit and un-dimensional. From these results, it can be concluded that there were satisfactory internal consistencies of the factors and all the factors are reliable.

Factors	Sub-	Estimates	Squared multiple	Average	Composite	Average	Maximum
	factors	(Standardised)	correlations (R <sup>2</sup> )	variance	Reliability	shared	shared variance
				extracted (AVE)	(C.R)	variance (ASV)	(MSV)
SF	CEI	0.527	0.316	0.536	0.659	0.247	0.232
	TEI	0.789	0.325				
	DM	0.606	0.298				
	DC	0.413	0.687	-			
	DU	0.894	0.256	-			
	IT	0.658	0.587	-			
SO	SIIS	0.498	0.695	0.632	0.697	0.230	0.115
	AGW	0.632	0.274	-			
	SRP	0.678	0.365				
	ITS	0.736	0.701	-			
	CU	0.632	0.695	-			
SPDDS	ICT	0.623	0.786	0.613	0.559	0.270	0.362
	UD	0.875	0.631				
	DDS	0.632	0.769	-			
	SR	0.724	0.554	-			
	LDU	0.981	0.627	-			
EM	ES	0.695	0.963	0.265	0.661	0.251	0.102
	ET	0.732	0.721				
	EE	0.695	0.698	-			
CS	CSRMP	0.632	0.620	0.298	0.754	0.32	0.118
	RM	0.907	0.702	-			
	RA	0.696	0.632	-			

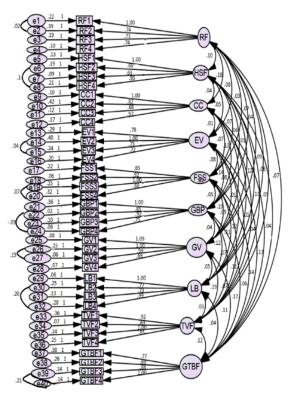


Figure 4 First-order CFA Measurement Model

#### 7. FRAMEWORK FOR THE SMART DAIRY INDUSTRY

Due to its ability to provide a visual representation of the results through the sophisticated analysis of several factors, SEM has gained popularity as a tool in business research. Its ability to identify and create a framework of variables that describe the indirect effect of certain independent variables onto a dependent variable through the mediation of a third variable accounts for much of its success and advantages. This leads to a path analysis that illustrates the series of variables through which causal effects may influence dependent variables and constructs.

It was identified as a latent variable using SF's factor scores, which were derived from the corresponding six measured variables (Table 2) and their factor loadings, which were acquired from the CFA that was done.

Despite being undoubtedly an approximation, this allowed for a valid estimate of the direct and indirect influences of the components under consideration on the framework as well as a strong model fit for the SEM analysis. Both methods—with and without the twenty measured variables of the Framework—were used in the SEM analysis that was carried out for the proposed framework's validation to further confirm this approximation.

Therefore, it was permissible and provided several benefits to employ the latent variables with their component scores as real variables in the SEM analyses:

- 1) The use of latent variables enhanced the model's fit and mitigated the impact of potential errors associated with the choice and construction of particular items and the survey's layout.
- 2) The derived latent variables function as overarching quantities and more accurately capture the key concerns related to the success and failures of the Industry 4.0 framework's implementation.

The goal of the study of each of the six latent variables was to get a thorough grasp of the average influences of the linked elements on the effectiveness of the framework's implementation (across socioeconomic and organizational characteristics). The results were averaged, which made it possible and justifiable to utilize SEM. Consequently, the framework was developed and the model fits were quantitatively evaluated and determined.

To assess a measure's accuracy and make sure the measuring items capture the required data, validity testing is essential (Holmes-Smith, Coote & Cunningham 2006). Convergent and discriminant validity may be tested using CFA and SEM (Anderson & Gerbing 1988).

The proposed conceptual framework for the smart dairy industry in the Indian subcontinent (Figure 5) is designed on industry 4.0 design principles. The framework includes two major domains namely organizational and technological. The technological domain consists of Smart Factories, Smart Operations, Data-Driven Services, and human System Integration, whereas the organizational domain consists of employee and cyber security. The technological aspect of the framework proposes the genesis of smart factories for steady growth in the dairy industrial sector. The Smart factory concept consists of the inclusion of digital modeling, integration of all systems and subsystems, and inclusion of IIOT for smooth operations. It further advocates comprehensive automotive digital data collection in all fields with all system support of IT. The framework further proposes that smart operations need to have well-defined system integration with information sharing, data security, self-reacting processes, and data-driven services with complete integration with operations and product development, and customers. The smart products must have ICT add-on functionalities. The organizational structure side of frame framework includes employees, cyber security, and degree of strategy. The degree of strategy will guide proper investment and innovation management in the organization and smart factory in the technological domain. Moreover, innovation management gives a clearer comprehension of the overall development of the dairy industry. For both smart factories and smart operations innovation management provides An essential component in the overall growth of the dairy sector. The framework advocates human system integration with a combination of human requirements within system design during the initial phases of system design.

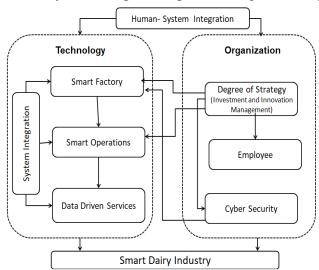


Figure 5 Framework for Smart Dairy Industry

### 8. CONCLUSION

To build a smart dairy industry there should be integration of data-driven services with the system, whether it's smart operations, maintenance, or delivery. The products of the dairy industry must follow a continuous process of testing the ideas with customers and the data collected should be used for making the design decision. The framework also proposes the combination of IT systems and comprehensive digital data collection with unique features of system integration.

For any dairy industry to implement Industry 4.0, there needs some detailed groundwork, including, an initial assessment of the proficiency level of a particular dairy industry to understand the starting position. This will assist in the identification of areas where efforts are required for improvement in maturity, which will further lay the foundation for successful adoption way for implementation. It is pertinent to mention that for any industry, it's very important to know the present status of maturity level. The reason is straightforward, most of the dairy industries are not yet prepared to implement Industry 4.0. To deal with this, the first step can be bringing the entire team to a single platform to share the plans for changes and adaptations. Adopting Industry 3.0 ideas as a foundation for Industry 4.0 necessitates team-

wide agreement on modifications and adjustments. Thus, getting managerial support needs to be among the first things you do on this voyage.

Secondly, the dairy industry has to elevate from the existing technological level by allowing the integration of systems, automation, and application of the Industrial Internet of Things (IIoT). Moreover, the dairy industry undergoing technological changes should begin with a small but smart start, initiating a Pilot plan followed by expansion at the entire facility. The pilot project plan will have fewer challenges to counter but will make the organization aware of the type of challenges. This will boost the morale of any organization including the dairy industry and will assist in successful implementation in the entire plant in a phased manner. Developing a strategy for an organization is an important component and this is the reason, the proposed framework for the smart dairy Industry (Figure 5) has considered this parameter. The strategy can be a short-term plan or a long-term plan depending on targeted objectives.

## **CONFLICT OF INTERESTS**

None.

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None.

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