Original Research

Determining the level of automation in the cosmetics industry considering new technology

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Abstract
Research shows that an increment in the levels of automation (LoA) can affect the quality of production, cost efficiency, and performance on a large scale. Increasing the levels of automation (LoA) is essential in this regard and automatization can help overcome the varying problems. This paper develops a new taxonomy to measure and increase the LoA in the cosmetics industry. The proposed taxonomy is presented as a five-dimensional (5-D) matrix. The rows correspond to the LoA considering new technology like Blockchain, Cloud, and Internet of Things (IoT) and the columns conform to Information, Plan, Act, Control, and Decision. This taxonomy can help managers clearly define LoA and according to the main factors in the cosmetics industry increase the current LoA with the use of the current resources. Also, the DYNAMO++ methodology was employed to measure the current LoA of a cosmetics factory and three sets of suggestions were considered to increase the LoA in the factory at issue. These suggestion sets were then compared to each other in terms of key parameters of cost, productivity, quality, and processing time via simulation.

Keywords- Levels of automation, Cosmetics industry, DYNAMO++, IoT, Cloud computing.

INTRODUCTION

Automation is enforced and designed to utilize the benefits of humans and the systems and autonomy are designed to achieve the functions of the system individually, operating well under important uncertainties for continued periods with limited or absent communication and with the capability to pay for system failures, all without external interference *(Vagia et al., 2016).* The interactions between humans and systems are defined through different levels of automation (LoA). The LoA is defined as the degree of automation, system technology, or task allotments between humans and machines *(Salmi, 2016).* Each level of LoA indicates a different degree of performance by the system. An Automation system can be planned and constructed in a way that secures the best option for the potentialities, profits, and disadvantages of humans and machines, but the LoA can vary between human beings or the system which does the whole job *(Sheridan, 1992).* On the other hand, in recent years, many changes have been made in technology, such as Blockchain and IoT. The effect of new technology is not considered in LoA taxonomy. The cosmetics Process Contains three subprocesses: Making, filling, and Packaging. Packaging is usually done manually in Iran. The possibility of virus transmission to products in manual processes of cosmetic production through infected workers is high in case of non-compliance with health issues. Moreover, the possibility of contamination of workers due to contact with other workers in the environment is high in manual processes.

Although running automation is inevitable in many industries, higher levels of automation will lead to high costs (Ojha, 2014) and complexities in the long run in some countries and may not be feasible for some factories. Different industries have unique features and if they are not taken into account in determining the appropriate levels of automation, their needs will not be accomplished. It should be noted that the definitions proposed for the LoA do not focus on any special industry and so the specific features of special industries have not been taken into account in this regard. This is because these definitions have generally been presented based on aircraft automation.

The cosmetics industry has notable properties, regarding its relevance to people's health and hygiene, and using automation is essential for improving its quality. However, the high cost is a big barrier to the full implementation of automation in this industry. By presenting a precise definition for automation in the cosmetics industry, it would be possible to help managers choose an appropriate LoA; in this way, they can determine the optimal LoA for their organizations, considering important parameters of automation and resources. In this paper, after studying the manufacturing process in the cosmetics industry, a new taxonomy is developed to determine and measure the most appropriate LoA. The results of this research are performed at a factory that produced cosmetic products in Iran, and the validity of the findings has been confirmed by experts.

The next sections of this research are organized as follows. In section two, a review of past works on the LoA and different taxonomies is proposed and how to determine the LoA is discussed. This is followed by the statement of the problem in section three. In section four, the methodology and model are introduced. In section five, the proposed model is applied to a case study to demonstrate the LoA. At last, section six arranges conclusions and makes recommendations for further research.

LITERTURE REVIEW

This section discusses a review of past works on the LoA. At first, LoA and its applications, as well as, its taxonomies have been discussed. In the next section, we paid attention to the dynamo methodology to determine the optimal level of automation

1. Levels of automation/autonomy

In automatic systems, the machine executes the preprogrammed commands without any functionality for selecting or making decisions, on the other hand, autonomous systems are able of recognizing different situations and making a decision respectively *(MahmoudZadeh et al., 2019).* Automation is fully related to autonomy and is an aim to reach, but generally, it is taken as equal to autonomy *(Schneider, 2016).* Most researchers see automation and autonomy as the same but *Fereidunian (2007)* and *Parasuraman (2007)* make a difference between the LoA and automation. Determining the LoA has many applications in industries for example in teleportation systems, remote control activities, and aircraft control. Table 1 presents this categorization *(Vagia et al.,2016).*

TABLE 1
DIFFERENT TAXONOMIES PRESENTED

Author	Application	Autonomy/Automation
Endsley (1987)	Cockpit system	Automation
Sheridan and Verplank (1978)	Avionics	Autonomy/Automation
Endsley (1987, 1997, 1999)	Teleoperation system	Automation
Ntuen and Park (1988)	Telerobot control	Automation
Riley (1989)	No specified application	Autonomy/Automation
Burtnyk and Greenspan (1999)	Telerobot control	Automation
Parasuraman (2000, 2005, 2007)	Avionics	Autonomy/Automation
Lorenz et al. (2001)	Space lift teleportation	Autonomy/Automation
Proud et al. (2003)	Space lift	Automation
Fereidunian et al. (2007)	Power distribution	Autonomy
Clough (2012)	DoD unmanned aerial vehicles roadmaps	Autonomy
Balfe (2015)	Rail signaling domain	Automation
Vagia et al. (2016)	No specified application	Autonomy/Automation
Habib (2017)	Supervision	Automation
Cabrall et al. (2018)	Vehicle	Automation
Mehta and Subramanian (2019)	Autonomous ships	Autonomy
Poornikoo (2022)	MASS	Automation

Different functions of industries have an important role in determining the level of automation. In this way, *Sheridan & Verplank (1978)* defined ten LoAs based on six functions that an operator or a system carries out in teleoperation control, i.e. getting, selecting, starting, requesting, approving, and telling. At the lowest level, humans do all the activities and at the intervening levels some processes are done by humans and some others by the system; at the last level, however, all operations are done by the system alone. *Endsley (1987)* defined four LoAs for advanced cockpit systems based on the four functions of suggesting, concurring, vetoing, and acting. Later, *Ntuen and Park (1988)* defined five LoAs by adding a fully manual level to the taxonomy proposed by *Endsley (1987). Burtnyk and Greenspan (1991)* defined five LoAs considering the role of the operator in telerobot control. At the first level, the operator is the sole controller of the robot; at the second level, the robot is remotely controlled by the operator; at the third level, the operator acts out the tasks, and the robot helps the operator; at the fourth level, the operator remains in the system but does not do anything, and at the fifth level the operator is removed from the system.

Endsley (1999) defined five LoAs, focusing on problems that degrade performance at the time of failure, and added the presence of the operator to improve the functionality of the system. At the first level of his taxonomy, all work is carried out by the operator fully manually. At the second level, the system proposes to do the work. At the third level, the work is done with the operator's approval. At the fourth level, if the operator does not reject the proposed option, work is automatically performed by the system and at the fifth level, everything is entirely done by the system. Draper *(1995)* proposed another taxonomy with five levels. At the first level of his taxonomy, work is fully manual and performed by the operator. At the second level, work is done manually with the aid of system intelligence. At the third level, tasks are controlled jointly by the operator and the system. At the fourth level, the system and the operator work together and at the fifth level, tasks are performed under the supervision of the operator. The LoA taxonomy by *Endsley (1999)* had ten levels in the context of teleoperation. In his taxonomy, five of the operations are performed by the operator and others by the system. It should be noted that *Lorenz et al.* (2001) defined automation at three levels. At the first level, the operator works only. At the next level, the system proposes to carry out work, but work is done by the operator and at the third level, if the operator does not decline, the system performs tasks. In Clough's (2002) taxonomy, however, there are four LoAs. The first level is fully manual, the second level is remotely controlled by the operator, the third level supports the decision, and the fourth level is fully autonomous. *Fereidunian et al.* (2007) proposed an eleven-level taxonomy by adding a level to the taxonomy by *Sheridan* (1992).While all previous articles focused on only one dimension, *Riley* (1989) and *Proud et al.* (2003) developed multi-dimensional models. *Riley* (1989) proposed the use of intelligent systems in determining the LoA. He propounded a two-dimensional matrix, the rows correspond to twelve LoAs while the columns referred to seven LoAs. In this matrix, the intersection of rows and columns is where the status of automation is determined. Nevertheless, *Proud et al.* (2003) defined eight LoAs, tailoring each LoA scale to fit the tasks covered by a function type observe, orient, decide, and act.

Vagia et al. (2016) reviewed all the previous definitions and provided a new definition with eight LoAs. In their definition, the first level was completely manual. At the second level, the system could provide various decisions. At the third level, the system presented the choices. At the fourth level, the system selected one decision and executed it with human approval. At the fifth level, the system performed the decision and informed the human. At the sixth level, the system executed the selected decision and informed the human only if asked. At the seventh level, the system executed the decision and informed the human. At the eighth level, the system did everything without human notifications, except in case of an error not existent in the previous specifications in which case the system needed to inform the operator. *Mehta and Subramanian* (2019) presented another definition of LoA related to autonomous ships. In this definition, the first level is decision support, the second level is an automatic process, the third level is constrained autonomy and the fourth level is full autonomy. Endsley (2017) paid attention to the challenges that system autonomy had for human supervisory controllers. He presented the model of human–autonomy system oversight that described the relationship between system autonomy characteristics and human cognitive functions and performance for gaining successful oversight and intervention. *Habib* (2017) developed an approach based on a human and machine collaboration model used to recognize various interactions between humans and machines and finally presented the LoAs. The definition proposed by *Parasuraman* (2000) was used by Balfe to define levels assigned to the rail signaling domain (2015). Cabrall et al. (2018) suggested a four dimensions LINT definition for vehicle action containing control across multiple concurrent dimensions of (1) Location (from local to remote), (2) Identity (between human and computer), (3) Number of factors (degree of centralization of control), as well as (4) adaptive optimization during the time. The best definition of LoA was done by the Society of Automotive Engineers (SAE) for the automotive industry. In this definition, the zero levels were no automation. The first level was driver-paid assistance, the second level was partial automation, the third level was conditional automation, the fourth level was high automation and the last level was full automation (2018). Finally, An approach is presented by *Westin, C., Hilburn, B, and Borst, C.* (2019). They presented a taxonomy containing seven levels varying from total human control to autonomy for air traffic control. Recently, Poornikoo (2022) presented the current status of LoA in autonomous ships and suggested a new definition to address the defects of existing LoAs. LoAs in ships were defined based on LoAs in practical tasks and functions. Als,o, Jayasekara (2021) compared the LoAs in different aerospace composite manufacturing progress chains to find where the LOA success and shortage.

2.DYNAMO methodology in the LoA

A methodology developed to measure and analyze the LoA in the manufacturing process is DYNAMO, which defined seven levels to detect the LoAs *(Frohm,2005, 2008)*. DYNAMO was presented to measure the LoA in the new manufacturing process. This method measures the levels of mechanical automation and information automation. This methodology has eight steps: planning, case study, documenting the process, analyzing the main tasks in the process, analyzing the sub-tasks, measuring the LoA, specifying maximum and minimum LoAs, analyze and documenting the results *(Frohm, 2007). Gorlach and Wessel* (2007) investigated the optimal LoA using *Frohm's* (2007) method at the

Volkswagen plant and selected the optimal level of production considering the cost, flexibility, and quality of production. Their research is purely computational in a complex industry and has only focused on the manufacturing aspect of the problem. After that, *Fasth et al.* (2008) suggested a verified DYNAMO which they called DYNAMO++. DYNAMO++ has twelve levels that are classified into four main steps counting the *initial study*, *measurement*, *analysis*, and *implementation* (Fasth et al., 2008). They followed their study (2009, 2010) and calculated and analyzed automation levels in the assembly industries using DYNAMO++. The optimal LoA was specified concerning efficiency and cost and simulated and then the results were explained. In this research, the appropriate degree of automation was first calculated and then evaluated using the dynamo methodology over a 12-step period. After system modifications, the degree of automation was recalculated. They also determined the current LoA in six industrial groups through the use of the DYNAMO++ methodology. In their study, the parameter that plays a key role in changing the LoA is processing time. They also concluded that changing the LoA is not always necessary. Then many authors used the DYNAMO++ in their study: *Lindstrom* (2010) explored the alignment between manufacturing strategy and decisions regarding the LoA using the DYNAMO++ and concluded that this alignment is ad hoc. *Choe et al.* (2015) used the DYNAMO++ to determine the role of automation on product flexibility in the truck's body production line. Then *Schneider and Andersson* (2016) used the DYNAMO methodology in a wood processing company and modified the production line. (Frohm, 2007). *Mehta & Subramanian* (2019) studied the barriers that a factory would face while increasing the LoA in an assembly workstation. In this, they measured the current LoA for an assembly using the DYNAMO++ methodology and then analyzed the results. Hadi and Brillinger (2020) found that using high-quality and high-variety production is expensive. They studied an optimal LoA that is practical and used technologies that were feasible to implement in the assembly workstation using the DYNAMO methodology (Frohm, 2007). *Huegli* (2020) used X-rays and examined 122 airport security screeners using the support of explosives detection systems for cabin baggage screening with low LoA. He found that the benefits of low LoA depend on unaided performance and automation reliability.

3. Motivation and contribution of the research

In most papers, it is mentioned that the highest level of automation is fully executed by the system, the lowest level is completely manual, and the automation levels are generally performed in the aviation industry. After study literature review we found that there has been no research to determine the optimal LoA in the cosmetics industry. Today, in the cosmetics industry, regarding its particular situation, manual activities are associated with many dangers and it is completely possible to carry out the whole production activities entirely by the system. Therefore, the presentation of a new model and the necessity of quality control are essential taking into account the status and risks existing during the production process, the resulting injuries, and losses.

In determining the level of automation, not only operation stages but also information stages are important; but most papers have focused on operations and the information dimension has not been considered. So, this paper provides a multidimensional model that includes operational and non-operational dimensions such as *Information*, *Plan*, *Act*, *Control*, and *Decision* to determine the LoA. Taking the proposed definition of automation from different respects into account and considering the weak points in the process of production with precision and clarifying each dimension in this process separately, appropriate actions should be done to improve the LoA regarding the current situation of the world. It should be noted that most managers in Iran do not have a clear-cut understanding of their automation levels. By using a multi-dimensional model, we can give them a comprehensive and precise perspective of their current production condition; this can improve the lower LoAs about the importance of this matter for the managers of these organizations. For example, in the process of production, because quality control is considered the main factor, we can pay more attention to this dimension of automation than other dimensions. Nagar (2013) stated in a study that a firm can identify weak human-related issues in its organization. As Nagar has pointed out, by recognizing the weak points in human-related tasks in companies and finding the problematic shortcomings we can automate the weak items. Hence, in case of a lack of enough budget, managers can improve the quality and profit of their organization by improving the levels of automation. This has good applications for management strategy as well. This will lead to health and safety and financial returns *(Kosciejew,2020).*In this regard, the following contributions are considered in this work: Determining the level of automation in the cosmetics industry with 5 dimensions.

- Measuring the current LoA using the DYNAMO++ method in the cosmetics industry with the new definition.
- Selecting the optimal LoA in the cosmetics industry using simulation.

RESEARCH QUESTIONS

The present study seeks to propose a new taxonomy of automation in the cosmetics industry considering the parameters specific to this industry. Three questions guided the study:

1. What is an appropriate taxonomy of LoA for the cosmetics industry?
2. What is the current LoA in the cosmetics industry?
3. What is the best LoA in the cosmetics industry?

This study is innovative in that it takes account of the specific characteristics of the cosmetics industry and is, therefore, able to decide more precisely on the optimal LoA. In this regard, the following assumptions are considered in this work:

1. The present study is in the cosmetics industry considering the parameters specific to this industry.
2. The production consists of the layers of the customer, sales, product inventory, quality control, manufacturing, material inventory, purchase, and waste inventory.
3. Quality control is considered a major dimension.
4. The framework of the paper is schematically presented in Figure. 1.

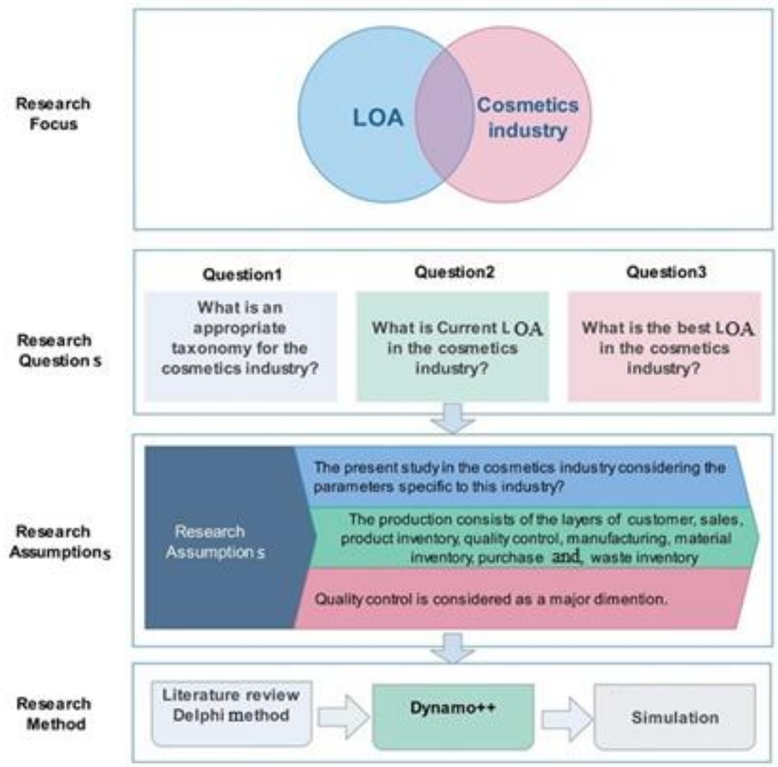


FIGURE 1
THE FRAMEWORK EMPLOYED IN THIS RESEARCH

THE METHODOLOGY FOR DETERMINING THE OPTIMAL LOACO

Several steps have been taken to answer the research questions. At first, an initial taxonomy was developed for the manufacturing process in the cosmetics industry. For this purpose, the parameters that affect manufacturing were defined and composed of the dimensions of the proposed taxonomy; then, for each dimension, four LoAs were defined. The proposed taxonomy model was validated and compared to *Sheridan and Verplank`s* model *(1978)*. The methods used during the research process are as follows.

1.Delphi

Delphi is a method based on the consensus of experts; it is used to design and evaluate automation levels for the cosmetic industry in this paper. The main idea in Delphi is that the expert group can provide more accurate opinions than a particular expert. In the Delphi process, after defining the research problem, a questionnaire is designed and sent to a panel of experts with a specialized and empirical background relevant to the research. After receiving the answers, the researcher makes changes to the model and questionnaire, based on different experts' opinions, and sends it back to the panel of experts. This will continue until a final consensus is reached. Finding a way to know if there is a consensus among experts is an important issue.

In the present study, according to *Schmidt (1997)*, Kendall's coefficient *(Kendall, 1997)* of concurrence (Kendall's W) which is a nonparametric statistic, is used to examine the consensus. Kendall's method is chosen because it can provide a unique answer, is easily computable, and also has a high level of understanding. In this method, Kendall's W is computed per round, and based on the value of this statistic, the amount of expert consensus is determined. The following is the procedure of the Delphi method used in this paper:

1. Set the eligibility criteria for the panel of experts;
2. Identify the experts based on the expert criteria and invite them to form a panel;
3. Design a questionnaire to evaluate the degree of compliance of experts with the proposed dimensions and levels of automation;
4. Send the questionnaire to the panelists;
5. Receive answers containing expert opinions;
6. Estimate the degree of consensus of experts following the proposed dimensions and levels of automation by calculating Kendall's W coefficient as follows: *(Kendall, 1997)*:
7.

a. Compute S by $S = \sum_{i=1}^{n} (R_i - \bar{R})^2$

b. Calculate correlation factor T by $T = \sum_{k=1}^{g} (t_k^3 - t_k)$ where t_k is the number of tied ranks in each k of g set of ties

c. Obtain Kendall's W using $W = 12S / (m^2(n^3 - n) - mT)$ where n is the number of items and m is the number of judges

8. If W is not large enough, the consensus is not reached, make changes to the dimensions and levels of automation and resubmit the newly designed questionnaire to the experts;
9. If W is large enough (see Table 2), the consensus is reached; terminate the Delphi process *(Schmidt,1997).*

TABLE 2
Interpretation of coefficient values of Kendall's W

W	Interpretation	Confidence in the order of factors
0.1	Very weak consensus	None
0.3	Weak consensus	Low
0.5	Medium consensus	Medium
0.7	Strong consensus	High
0.9	Very strong consensus	Very high

In this way, a questionnaire was developed to seek the opinion of a panel of experts on the propounded taxonomy following the Delphi method. This Likert-scaled questionnaire consisted of 10 items, with each item being followed by five answer choices: 'Very Highly Effective', 'Highly Effective', 'Moderately Effective', 'Minimally Effective', and 'Very Minimally Effective'; 'Moderately Effective' was taken as the neutral choice. To reach an acceptable consensus, it was necessary to select qualified, experienced, and expert persons capable of delivering critical and distinct input on the subject of LoA in the cosmetic industry. Thus, a panel of 29 experts in the ground of industrial automation and cosmetics was formed. Panel members from 16 universities and research centers as well as research and development centers of 4 factories in the cosmetic industry were invited and selected based on two or more of the following criteria:

1. Sufficient facts for publication of papers related to industrial automation and the cosmetic industry in blind peer review journals in Iranian or international publications. (e.g. number of papers, number of citations);
2. Experience and participation in the development and management of industrial automation projects in the cosmetics industry;
3. Experience and participation in production lines, quality control units, and product health assurance in the cosmetics industry.

Accordingly, twenty-six persons were selected as panel members. The other three were composed of two specialists in the field of chemical continuous production; one dermatologist was also chosen. To determine the extent to which the experts agreed on the questions in the questionnaire, the mean, standard deviation, and Kendall rank correlation coefficient (τ) were used. If the value of this coefficient does not change significantly from one round to another, running the Delphi method should be stopped. The value of significance was set at 0.05. Invitations were sent out to forty-seven experts to take part in the study, but ultimately only twenty-nine participated in this part. The taxonomy and the questionnaire were distributed and collected electronically for fourteen days in February 2019 in three rounds adopting the Delphi method. In each round, the taxonomy was modified and sent back (together with the modified questionnaire) to the experts to seek their approval.

2. DYNAMO++

After finalizing the proposed taxonomy, it was used to measure the current LoA at a factory in Iran, a producer of various cosmetic products, using the DYNAMO++ methodology. DYNAMO++ includes four main phases: study, measure, analyze, and implement *(Frohm, 2008)* which are presented in Table 3.

TABLE 3
DYNAMO++ METHODOLOGY

Phase	Steps
Study	Choose a case study
	Begin the process
	Recognize flow and time parameters (VSM)
Measure	Recognize main operations (HTA)
	Measure the LoA (mechanical and cognitive)
	Write the results
Analyze	Choose the minimum and maximum LoAs for the identified operations (workshop)
	Design the square of possible improvements (SoPI) based on the results of the study
	Analyze the SoPI
Implement	Imagine suggestions for improvements
	Implement the suggested improvements
	Check the implementation

For verification purposes, the current LoA was also measured using the model propounded by *Sheridan and Verplank* (1978).

3. Simulation

After phases of the initial study, measurement, and analysis, as well as drawing upon the opinion of experts and our knowledge, three sets of suggestions- namely expert, low-cost, and costly but profitable- were defined to improve the LoA in the factory under discussion. The Dynamo++ implementation phase must be applied to understand the outcome of each suggestion set. The implementation phase in Dynamo++ can be done using simulation. Simulation is the creation and development of a computer model of a systematic process to evaluate and test improvement suggestion sets. Enterprise Dynamics (ED) is an object-oriented software for simulating and controlling dynamic and discrete processes in an organization. With this software, users can select their model elements called Atom from the standard library section and create their simulated model. ED is an efficient and flexible tool for system simulating and random event analysis that plays a significant role in reducing the risk of new developments in organizations. Design and development with simulations are also important factors to be considered by manufacturing organizations *(Narula,2020)*. For this aim, the suggestion sets were measured according to the key parameters such as ccost cuts increased productivity, improved quality, and reduced processing time by simulating the production lines after the incorporation of the suggestions. The steps to perform the simulation are as follows:

1. Design product line mode based on the product line and proposed suggestions;
2. Determine the key parameters to use in the simulation process;
3. Simulate the three sets of suggestions using the ED software;
4. Measure the parameters of cost, quality, time, production quantity, and ultimately profitability;
5. Compare results.

The overall research procedure is schematically presented in *Figure. 2*.

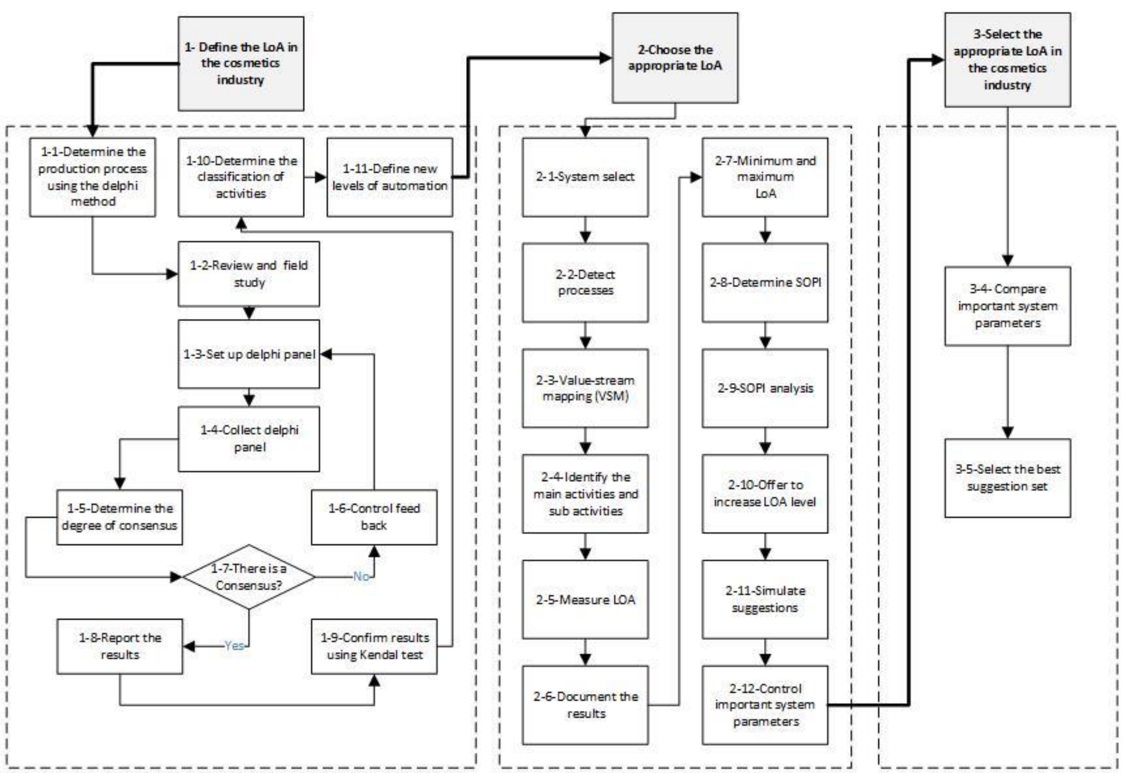


FIGURE 2
THE METHODOLOGY DEVELOPED IN THIS RESEARCH

RESULTS AND DISCUSSION

In this part, the proposed methodology is described to provide sufficient details to enable us to answer three research questions for the cosmetics industry.

1.The appropriate taxonomy of automation for the cosmetics industry

The main steps involved in the manufacturing process of the cosmetic industry (*Fig.3*) were determined after studying the different production lines in the cosmetics industry and interviewing twenty-nine experts and manufacturing executives. In process of production, the sale plan is provided first and on its basis, the production plan is prepared considering the preliminary stock of the inventory period. After that, the plan for buying raw materials and packaging regarding stock inventory and the raw material needed for production should be provided for the bill of material. Then the main process of production including three workstations, i.e. making, filling, and packaging gets started. In the manufacturing workstation, bulk is provided by the reactor and in the filling workstation bottles and tubes are filled with it. In the packaging workstation, tubes and bottles are packaged in boxes and transferred to inventory. Waste is sent to waste inventory. It should be noted that quality control is done throughout all these steps.

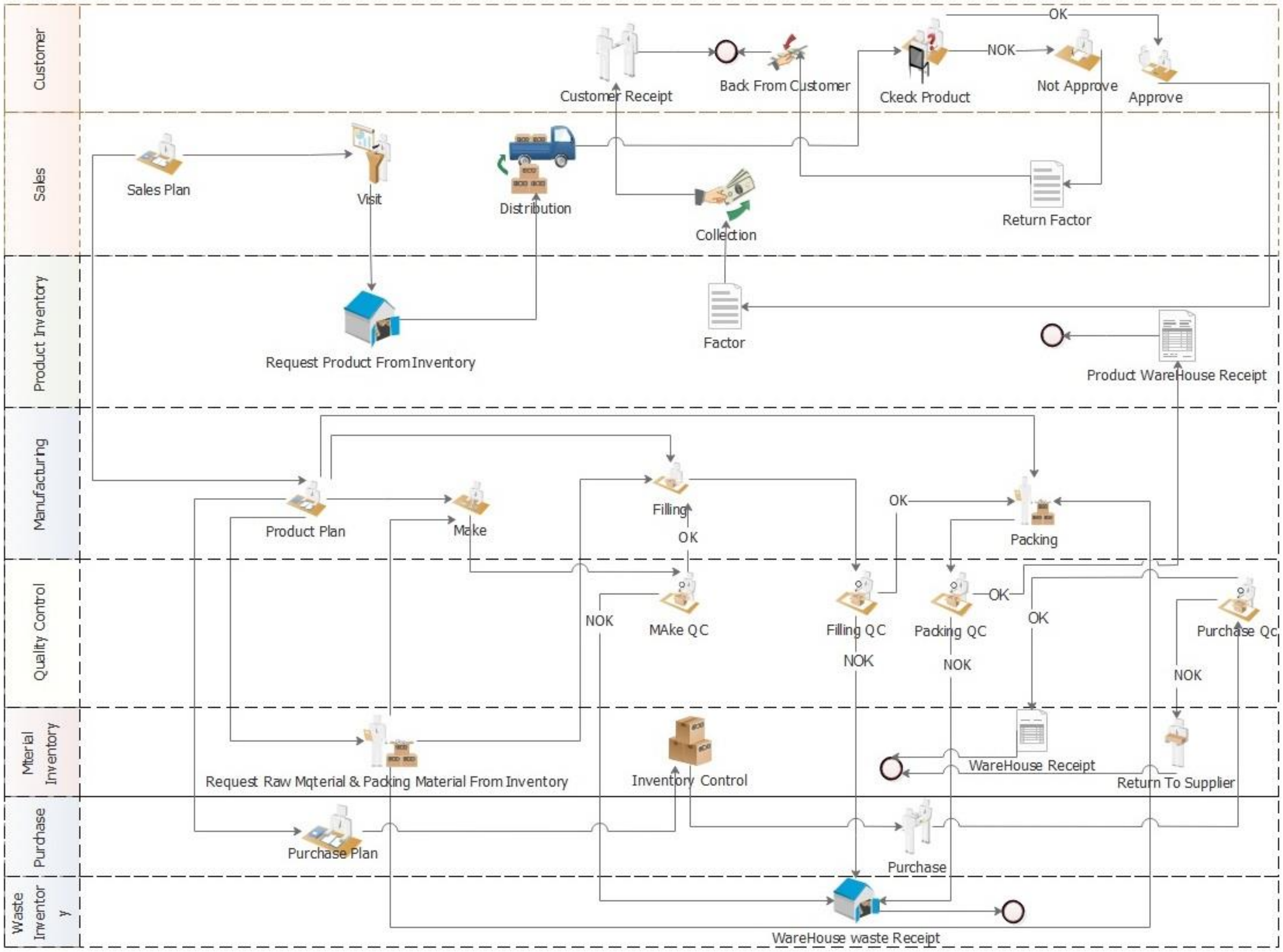


FIGURE 3
THE MANUFACTURING PROCESS OF THE COSMETICS INDUSTRY

The results of the three rounds of the Delphi method are given in Table 4. The fact that the value of the Kendall rank correlation coefficient in the third round was more than in the second round by only 0.45 shows that the levels of agreement among the experts were not considerably different in the two rounds. For this reason, the Delphi method stopped after the third round. The weight in the final round of the Delphi method was W = 0.704, implying a strong agreement among the experts on the factors under study.

TABLE 4
RESULTS OF THE DELPHI METHOD

Activity	First-round		Second-round		Third-round	
	Mean	SD	Mean	SD	Mean	SD
Confirmation of the manufacturing process	4.1	0.84	4.2	0.59	4.3	0.46

It is worth noting at this point that two processes related to maintenance were removed and the sales process was changed minimally according to the comments of the experts. The activities process was broken down into five dimensions: collecting and processing information ("*Information*"), planning ("*Plan*"), implementation ("*Act*"), controlling ("*Control*"), and decision-making ("*Decision*"). Subsequently, for each dimension, four LoAs were defined in Table 5. As can be seen in *Figure.3*, planning and controlling are the main parts of the production process. We need information for all activities. The decision is also another important dimension that is repeated in all activities (*Fig.3*). The dimension of implementation ("*Act*") can be done by the operator or the system. For example, in the filling workstation, the action of filling the tubes or bottles can be done by system or manually, or both. After identifying the dimensions and verification by the expert panel, different LoAs which included fully manual, semi-manual, semi-automated, and fully automated levels were defined based on studies done in factories (Table5).

TABLE 5
A NEW TAXONOMY FOR THE LOAS IN THE COSMETICS INDUSTRY

Dimension	LoA	Description	Explanation
Information	Level 1	Fully manual	The human gathers, filters, ranks, and processes data.
	Level 2	Semi-manual	The computer and human gather filter and rank data but only the computer processes data and displays all information from the Local Area Network (LAN) network or system.
	Level 3	Semi-automated	Information is collected partly by humans and partly by the system and the computer filters, ranks, and processes data and displays all information from the Cloud.
	Level 4	Fully automated	The computer gathers, filters, ranks, and processes data from the Blockchain. The computer uses all existing data from different data sources.
Plan	Level 1	Fully manual	Only the human plans.
	Level 2	Semi-manual	The system plans and the human can change the results and some planning is done only by the human.
	Level 3	Semi-automated	Planning is done by the system based on information gathered by the system but it needs human approval, i.e. vertical integration is used to make the production planning and execution more dynamic. In other words, dynamic planning, control, and execution are vertically integrated and interconnected.
	Level 4	Fully automated	Planning is done by a system without human approval based on information gathered by the system. Decision support is used for predictive planning and control of processes and/or the trigger of automated and subsequent processes.
Act	Level 1	Fully manual	Human acts by hand.
	Level 2	Semi-manual	Human acts using simple equipment.
	Level 3	Semi-automated	Human acts using programmable machines. The progressiveness of human-machine interaction is efficient and error-free.
	Level 4	Fully automated	The system acts using IoT. The performance of processes that are supported by the system contributes significantly to the flexibility of production. Faster data processing based on current data helps to achieve the goal of a fast reaction to changing requirements.

Dimension	LoA	Description	Explanation
Control	Level 1	Fully manual	The human control all activity and also quality control is done by a human.
	Level 2	Semi-manual	The human and system control activity, but quality control is done by the human using simple equipment. Fast reactions do changes that are on short notice.
	Level 3	Semi-automated	The system controls all activity, but quality control is done by humans using intelligent equipment, the result of which is the reduction of errors and an increase in efficiency. The system uses the data to trigger automated processes.
	Level 4	Fully automated	The system controls all activity and quality control is done by the system. The system has to be able to support end-to-end processes and exchange data.
Decision	Level 1	Fully manual	The human ranks tasks and decides everything.
	Level 2	Semi-manual	The computer ranks tasks and generates some decisions which are selected from and carried out if the human consents. The human may approve of the option or select another one.
	Level 3	Semi-automated	The computer ranks tasks and generates some decisions which are selected from and carried out if the human consents. The human can approve one of the options. The operator will be actively provided with decision-supporting recommendations based on algorithms that have been programmed beforehand.
	Level 4	Fully automated	The computer ranks tasks and generates decisions. A human cannot change their decision. Machine data such as quality information are collected by sensors during production and sent to the system. In this way, the product can be adjusted if quality issues occur. The system performs the decision support for predictive planning and the control of processes and/or the trigger of automated, subsequent processes.

The proposed taxonomy was validated and confirmed by the experts using the Delphi method, with the results presented in Table 6.

TABLE 6
RESULTS OF THE DELPHI METHOD FOR THE PROPOSED TAXONOMY

Dimensions	First-round		Second-round		Third-round	
	Mean	SD	Mean	SD	Mean	SD
Information	3.1	0.74	3.7	0.75	4.1	0.77
Plan	4.2	0.86	4.5	0.76	4.6	0.83
Act	4.3	0.78	5.1	0.75	7.1	0.80
Control	3.3	0.64	3.8	0.73	4.5	0.84
Decision	2.9	0.65	3.3	0.72	3.8	0.76

The propounded taxonomy was additionally validated by the taxonomy of *Sheridan and Verplank* (1978) the results of which are presented in Table 7. As Table 6 shows, level 1 of the Sheridan and *Verplank*'s definition is equivalent to level 1, and levels 7 to 10 of Sheridan and *Verplank*'s definition are equivalent to level 4 in the new LoA.

TABLE 7
THE VALIDATION OF THE PROPOSED MODEL BY THE TAXONOMY OF SHERIDAN AND VERPLANK (1978)

Sheridan & Verplank LoA		Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
Proposed LoA		Fully manual control	The computer offers a complete set of alternatives	The computer Offers a few alternatives	The computer suggests one alternative	The computer runs with human approval	The operator has the opportunity to veto	The computer runs after human knowledge	The computer informs the operator upon request	The computer informs the operator if necessary	Fully automatic control
Level 1	Fully manual										
Level 2	Semi-automated										
Level 3	Semi-automated										
Level 4	Fully automated										

2. Measuring the current LoA using the DYNAMO++ method

The current LoA at the factory understudy was measured using the proposed taxonomy and the model proposed by *Sheridan and Verplank (1978)* and adopting the DYNAMO++ methodology.

Phase 1: Initial study

In this phase, we studied the production lines of various cosmetic products and examined manufacturing processes, machinery, warehouses, and the method of handling raw materials, products, and semi-finished products between the production lines (Step 2). Then, value stream mapping (VSM) was performed to recognize the parameters that can influence production performance including production time, production volume, the amount of waste, and quality (Step 3). The result of this step is shown in *Figure.3.* In this regard, the opinions of production experts and managers were also sought.

Phase 2: Measurement

In this phase, hierarchical task analysis (HTA) was performed to break down the tasks into subtasks (Step 4). Then, the LoAs were measured for each task and subtask (Step 5). The results (Step 6) of measuring the current LoA at the factory under study, using the proposed taxonomy, are summarized in Table 8.

TABLE 8
THE MEASURING OF THE CURRENT LOA USING THE PROPOSED TAXONOMY

Main Tasks	Subtasks	Dimensions					Total
		Information	Plan	Act	Control	Decision	
CRM (customer relationship management)	Ordering	2	2	2	2	2	2
	Returning from customer	2	2	2	2	2	2
	Controlling	2	2	2	2	2	2
	Delivering	2	2	2	2	2	2
	Transporting	2	2	2	2	2	2
Sales	Sales planning	2	3	2	2	2	2
	Visiting	2	2	2	2	2	2
	Distribution	2	2	2	2	2	2
	Payment	2	2	2	2	2	2
	Pay factor	2	2	2	2	2	2
	Storage	2	2	2	2	2	2
Manufacturing	Loading and unloading	2	2	1	2	2	2
	Transporting raw material	2	2	2	2	2	2
	Storage	2	2	2	2	2	2
	Product planning	2	2	2	2	2	2
	Making	2	2	2	2	2	2
	Mixing	2	2	2	2	2	2
	Filling	2	2	2	2	2	2
	Packaging	2	2	1	1	2	2
	Measuring	2	2	2	2	2	2
	Transporting products	2	2	2	2	2	2
Waste Disposal	Transporting waste	2	2	2	2	2	2
	Moving to waste inventory	2	2	2	2	2	2
Purchase	Purchase planning	2	3	2	2	2	2
	Buying	2	2	2	2	2	2
	Quality control	2	2	2	2	2	2
Inventory	Receiving	2	2	2	2	2	2
	Delivery	2	2	2	1	2	2
	Counting	2	2	2	1	2	2
	Storage	2	2	2	1	2	2

Phase 3: Analysis

In this phase, after holding a workshop with the production managers and engineers, the maximum possible LoA in each production area was determined (Step 7). Results from the workshop show that; the square of possible improvements (SoPI) was designed for all tasks and subtasks (Step 8). The SoPI matrix shows the current and the maximum possible LoAs for each task. A SoPI matrix for the model developed by *Sheridan and Verplank (1978)* is given as an example in *Figure 4*. As can be observed, the current level of both mechanical automation and cognitive automation in this production area is 3, but it can be increased up to level 10 (Step 9).

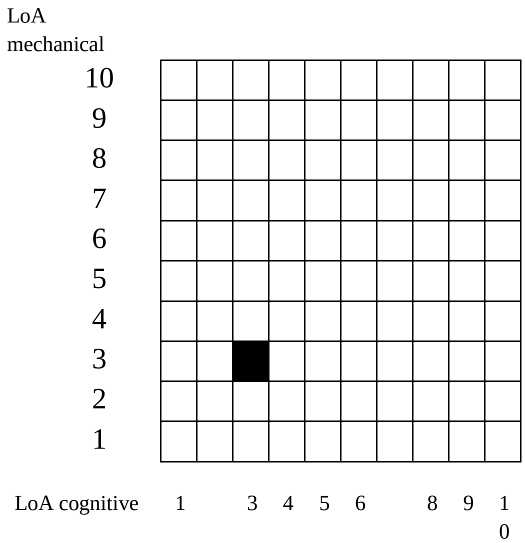


Figure 4
A sample SoPI matrix for the model by Sheridan and Verplank *(1978)*

As for our taxonomy, the SoPI of the same production area (Fig. 5) shows that for all five dimensions the current and the maximum possible LoAs are 2 and 4 respectively.

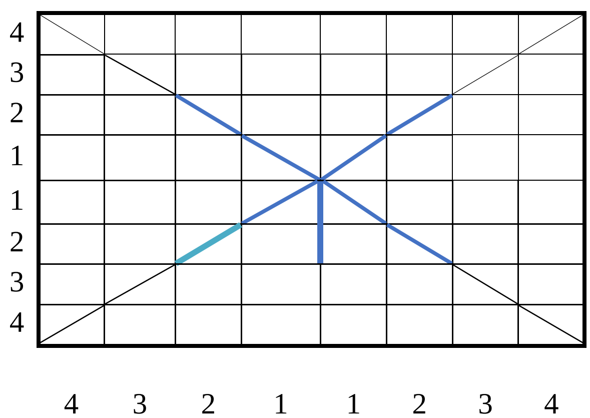


Figure 5
SoPI matrix for the proposed taxonomy

Phase 4: Implementation

After the SoPI matrices were reviewed and various workshops were held with the production managers and engineers, three sets of suggestions were used to increase the overall level in the factory under study according to the key industry parameters such as cost-cuts, increased productivity, improved quality, and reduced processing time as presented in Table 9 (Step 10).

TABLE 9
SUGGESTIONS MADE TO INCREASE THE OVERALL LOA IN THE FACTORY UNDERSTUDY

Suggestion set	Description
Current situation	The making, filling, and packaging lines are semi-automated.
Expert	Using conveyor belts to transport goods between workstations. Using pipes to transport raw materials from the warehouse to the making workstation.
Low-cost	Changing the current location of the filling and packaging lines. Using automated valves in the filling and making workstations.
Costly but profitable	Using new reactors directly connected to the warehouse. Using high-speed fillers. Using waterjets for washing the lines. Using high-speed packaging machinery. Using sensors in the filling lines to ensure thorough container filling.

For DYNAMO++ steps 11 and 12, the production lines were simulated after the incorporation of the three sets of suggestions using the ED software (*Fig. 6*). *Figure. 6* shows the three main source modes that enter the manufacturing field. The bulk is then transferred to the filling field and then to the final product packaging field. The QC oversees three production areas and delivers the final product to the warehouse and the defective product to the waste warehouse. The key parameters used in the simulation are shown in Table 10.

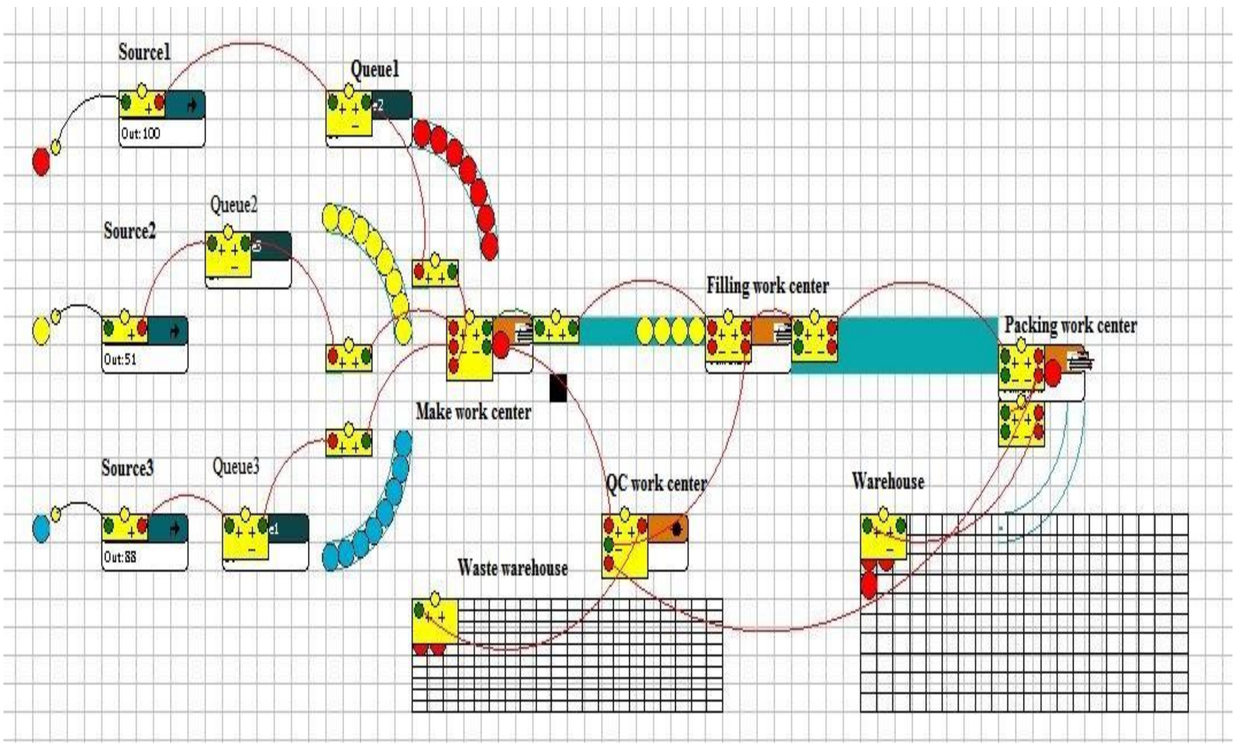


Figure 6
The environment of the ED software

TABLE 10
THE MAIN PARAMETERS USED IN SIMULATING THE THREE SETS OF SUGGESTIONS

Parameters	Notations for distributions	
Making workstation	N(μ,σ)	Normal distribution with mean μ and standard deviation σ
Filling workstation	Uni(a,b)	The discrete uniform distribution between a,b
Packaging workstation	Uni(a,b)	The discrete uniform distribution between a,b
QC workstation	LnN(μ,σ)	Long normal distribution with scale μ and shape σ
Warehouse		

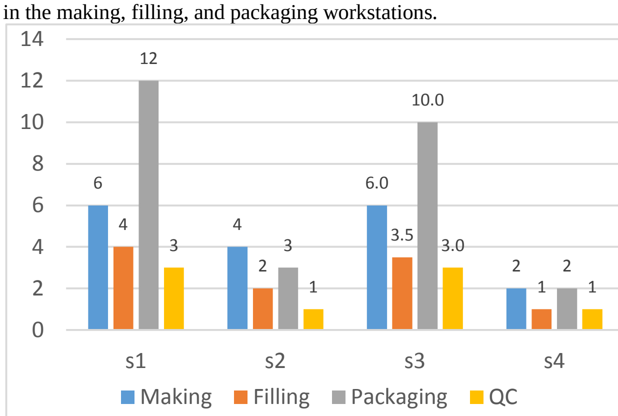
A making machine has a normally distributed daily output in units. The average daily output is 65 and the daily output standard deviation is 5. A filling machine has a discrete uniform distribution of daily output in units. The daily output is between 550 and 600. Also, a Packaging machine has a discrete uniform distribution of daily output in units. The daily output is between 500 and 600. A QC workstation has a long normally distributed daily output in units with scale 20 and shape 2. The results of simulating the implementation of the proposed suggestion sets are presented in Table 11 and Figure.7. As can be seen, all suggestion set improved automation by one level in the five dimensions of the proposed model. ***Table 11*** shows that in the expert suggestion set, the production time and the amount of product waste are slightly reduced. In the low-cost suggestion set, the amount of waste and the time of production are further reduced. In the costly but profitable suggestion set, although the production time remains approximately constant, the amount of waste is reduced. *Figure. 7* also shows the production time and the amount of waste produced in the areas of making, filling, packaging, and quality control. As is evident in the costly but profitable suggestion set, both the amount of waste produced and production time were greatly reduced. In *Figure. 7* the variations of the amount of waste, production time, and profit in the initial state of the workstation (s1) before the change, and the three suggestion sets (s2, s3, s4) are compared; it was found that the s4 suggestion set- costly but profitable- has the least waste, the least productive time, and the maximum profit.

TABLE 11
THE RESULTS OF SIMULATING THE THREE SUGGESTION SETS

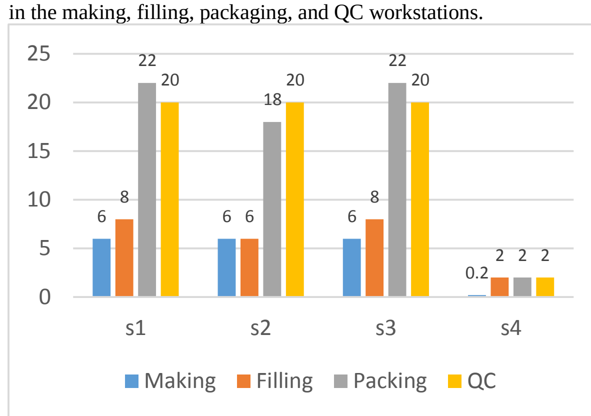
Runs	Runs 1-5			Runs 6-10			Runs 11-15			Runs 16-20		
Suggestion sets	Before change			Expert			Low-cost			Costly but profitable		
	T	P	W	T	P	W	T	P	W	T	P	W
Making workstation	6.0	64	6	4.0	64	6	6.0	64	6	2.0	64	0.2
Filling workstation	4.0	572	8	2.0	574	6	3.5	572	8	1.0	637	2
Packaging workstation	12.0	550	22	3.0	556	18	10.0	550	22	2.0	635	2
QC workstation	3.0	0	20	1.0	0	20	3.0	0	20	1.0	0	2
Warehouse		530			536			530			631	

T: Time; P: Product quantity; W: Waste quantity

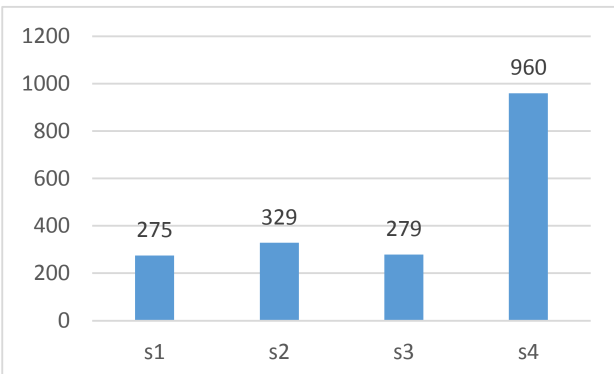
a. Changes in time production after implementing different suggestion sets(s1, s2, s3, s4) in the making, filling, and packaging workstations.



b. Changes in waste production after implementing different suggestion sets (s1, s2, s3, s4) in the making, filling, packaging, and QC workstations.



c. Changes in production profit after implementing different suggestion sets (s1, s2, s3, s4).



d. Changes in production quantity after implementing different suggestion sets (s1, s2, s3, s4) in the making, filling, and packaging workstations.

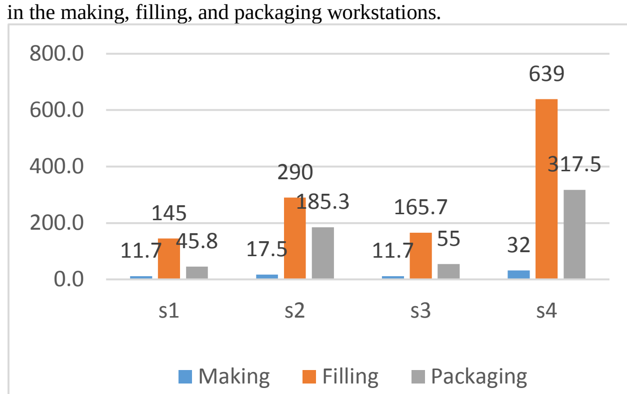


Figure 7. Change in parameters after implementing the suggestion sets s1(Before change), s2(Expert), s3(Low-cost), s4(Costly but profitable)

Table 12 shows the results of the simulation of the proposed suggestion sets and the initial state of workstations. In the costly but profitable suggestion set, the amount of waste, production time, and the number of workers in the workstations are lower. But the production quantity and profitability are higher.

TABLE 12
RESULTS AFTER IMPLEMENTATION OF SUGGESTION SETS

Suggestion sets	QC Time	Waste in making workstation	Break downtime	No. of workers	Production time (hours)	Production in 12 hours	Material cost $	Direct work cost $	Labor cost $	Training cost$	Equipment cost $	Profit for one-day production $	Setup time	Time out
Before change	4.5	6	3	10	22	289	0.375	0.15	0.1	0	0	275	0	0
Expert	4.5	6	2	8	9	714	0.3625	0.125	0.075	250	5,000	329	30	3
Low-cost	4.5	6	2	9	19.5	326	0.375	0.145	0.1	25	1,250	279	15	1
Costly but profitable	1.5	0.2	0	2	5	1514	0.325	0.0125	0.05	250	250,000	960	270	30

Expert suggestion set: Add a conveyor for material transfer between production and stock lines and material control valves
Low-cost suggestion set: Add material control valves
Costly but profitable suggestion set: Use the automatic line in all areas of production and warehouses

3. Selection of the best LoA

The parameters of cost, quality, time, production quantity, and ultimately profitability were measured after implementing the three suggestion sets. Table 13. The amount of waste in the *costly but profitable* scenario is very small. Also, the number of products produced is more than in the other scenarios. The amount of breakdown in the costly but profitable scenario is zero but the amount of setup time and time out is more than in the other scenarios. Scenario *costly but profitable* is the most appropriate option, after that the low-cost scenario and at last, the expert scenario is suggested.

TABLE 13
DECISION MATRIX

Value / SS	Waste in making workstation	Break downtime (h)	Production time (h)	Production in 12 hours	Equipment cost	Profit for a one-day production $	Setup time	Time out
S1	6.00	3.00	22	289	0	275	0	0
S2	6.00	2.00	9	714	5,000	329	30	3
S3	6.00	2.00	19.5	326	1,250	279	15	1
S4	0.2	0	9	850	250000	960	270	30.00

SS: Suggestion sets; S1: Current situation; S2: Expert; S3: Low-cost; S4: Costly but profitable
Hours: H

CONCLUSION

In the present study, to answer the first research question a model was developed to measure and improve the LoA in the cosmetics industry taking into account the specific characteristics of this industry and differentiating effective parameters at the LoAs. In the proposed model, the characteristics that impact the manufacturing process were defined as five dimensions, i.e. "*Information*," "*Plan*," "*Act*," "*Control*," and "*Decision*", and subsequently for each dimension four LoAs were defined. To answer the second research question this model was then employed to measure the current LoA at a cosmetics factory. Following this, three sets of suggestions were made to improve the LoA: "expert," "low-cost," and "costly but profitable". To answer the third research question the simulation of the production lines after the incorporation of these suggestions based on parameters such as cost-cuts, productivity, quality, and reduced processing time revealed that the “costly but profitable” suggestion set is the most appropriate alternative when attempting to increase the LoA. The results of this study indicate that breaking each LoA down into five dimensions would make it possible to measure each dimension separately and increase the LoA given the relative importance of each dimension. This helps us avoid needless expenses as it allows us to improve the more important dimensions to the exclusion of less important ones. Moreover, the choice of the “costly but profitable” suggestion set shows that improving the LoA will be profitable in the long run.

The contributions of this research can be summarized as follows: (1) The process of the cosmetics industry and its unique features have been fully recognized and its associated model was developed to develop the taxonomy of the level of automation; (2) The proposed model is multi-dimensional and could be used for operational and non-operational states of cosmetics industry; (3) A simulation is accomplished to develop management solutions to increase the LoA; (4) The proposed model of this study is applied on a real-world case study of cosmetics industry in Iran. This study helps managers to increase the LoA in the cosmetics industry and brings about a rise in production quantity and quality and a decrease in production time and waste. The findings of this research also help managers to decrease the transitions of viruses and especially reduce the hazards of infection of COVID-19 in the cosmetics industry. Most managers do not have a clear understanding of LoA in their organizations and the definitions proposed have not generally focused on a specific industry. This research helps managers in the cosmetics industry to measure the current LoA concerning the aforementioned dimensions in their organization. They can also enhance the LoA in their companies with the resources at hand. This is applied research that was designed according to the specific features of the cosmetics industry. The findings of this research can help organizations that cannot modify their LoA to the full extent to solve their problems with a limited amount of resources. It can be done in other manufacturing industries. It can have applications in the petrochemical and electronic industries, to name a few. This research can be extended in some ways: Some other factors can be used to compare different suggestion sets such as some parts, product volume, and also sustainability issues such as environmental and social dimensions of automation. Also, mathematical programming models can be employed to select optimal LoAs. We propose that future researchers use Six Sigma to select optimal LoAs to improve profitability and reduce defects *(Yadav,2019)*. Researchers can also measure manufacturing performance parameters after improving LoA in their organizations *(Singh, 2010)*. Also, incorporating sustainable practices in the manufacturing organization can be implemented by improving LoA in organizations *(Pathak,2020)*.

REFERENCES

[1] E. Petri, D.I.Y., Coronavirus Solutions Are Gaining Steam, 2020.
[2] Biagini, V., Subasic, M., Oudalov, A., & Kreusel, J. (2020). The autonomous grid: Automation, intelligence and the future of power systems. Energy Research & Social Science, 65, 101460.
[3] Burtnyk, N., & Greenspan, M. A. (1991). Supervised Autonomy-Partitioning Telerobotic Responsibilities Between Human Machine.
[4] Cabrall, C. D., Sheridan, T. B., Prevot, T., de Winter, J. C., & Happee, R. (2018, January). The 4D LINT model of function allocation: Spatial-temporal arrangement and levels of automation. In International Conference on Intelligent Human Systems Integration (pp. 29-34). Springer, Cham.
[5] Chiantella, N. (1982). Achieving integrated automation through computer networks. SME/CASA Computer integrated manufacturing series, 1(2), 2-21.
[6] Clough, B. (2002). Relating Autonomy To a Task: Can It Be Done? In 1st UAV Conference (p. 3445).
[7] Draper, J. V. (1995). Teleoperators for advanced manufacturing: Applications and human factors challenges. International Journal of Human Factors in Manufacturing, 5(1), 53-85.
[8] Duncheon, C. (2002). Product miniaturization requires automation–but with a strategy. Assembly Automation, 22(1), 16-20.
[9] E.Ackerman,Amazon uses 800 robots to run this warehouse, 2019, https://spectrum.ieee.org/automaton/robotics/industrial-robots/amazon-introduces-two-new-warehouse-robots (accessed: 15 April 2020).
[10] Endsley, M. R. (1987, September). The application of human factors to the development of expert systems for advanced cockpits. In Proceedings of the Human Factors Society Annual Meeting (Vol. 31, No. 12, pp. 1388-1392). Sage CA: Los Angeles, CA: SAGE Publications.
[11] Endsley, M. R. (1997, October). Level of automation: Integrating humans and automated systems. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 41, No. 1, pp. 200-204). Sage CA: Los Angeles, CA: SAGE Publications.
[12] Endsley, M. R. (2017). From here to autonomy: lessons learned from human–automation research. Human factors, 59(1), 5-27.

[13] Fasth, Å., Stahre, J., & Dencker, K. (2008). Analyzing changeability and time parameters due to levels of Automation in an assembly system. In Proceedings of the 18th conference on Flexible Automation and Intelligent Manufacturing-FAIM.
[14] Fasth, Å. (2009). Measuring and Analyzing Levels of Automation in assembly systems-For future proactive systems (Doctoral dissertation, Chalmers University of Technology).
[15] Fereidunian, A., Lucas, C., Lesani, H., Lehtonen, M., & Nordman, M. (2007, June). Challenges in implementation of human-automation interaction models. In 2007 Mediterranean Conference on Control & Automation (pp. 1-6). IEEE.
[16] Frohm, J. (2008). Levels of Automation in production systems. Göteborg: Chalmers University of Technology.
[17] Frohm, J., Lindström, V., & Bellgran, M. (2005, July). A model for parallel levels of automation within manufacturing. In 18th International Conference on Production Research (pp. 1-6).
[18] Granell, V., Frohm, J., Bruch, J., & Dencker, K. (2007). Validation of the DYNAMO methodology for measuring and assessing Levels of Automation.
[19] Gorlach, I. A., & Wessel, O. (2007). Case study: Automation Strategies at Volkswagen. In World Congress on Engineering (pp. 1062-1067).
[20] Gupta, U. G., & Clarke, R. E. (1996). Theory and applications of the Delphi technique: A bibliography (1975–1994). Technological forecasting and social change, 53(2), 185-211.
[21] Habib, L., Pacaux-Lemoine, M. P., & Millot, P. (2017). A method for designing levels of automation based on a human-machine cooperation model. IFAC-PapersOnLine, 50(1), 1372-1377.
[22] Hadi, M. A., Brillinger, M., Haas, F., & Weinzerl, M. (2020) Roadmap to an adaptive assembly line for e-axles.
[23] Heiko, A. (2012). Consensus measurement in Delphi studies: review and implications for future quality assurance. Technological forecasting and social change, 79(8), 1525-1536.
[24] Hoffman, R. R., Feltovich, P. J., Ford, K. M., & Woods, D. D. (2002). A rose by any other name... would probably be given an acronym [cognitive systems engineering]. IEEE Intelligent Systems, 17(4), 72-80.
[25] Huegli, D., Merks, S., & Schwaninger, A. (2020). Automation reliability, human–machine system performance, and operator compliance: A study with airport security screeners supported by automated explosives detection systems for cabin baggage screening. Applied Ergonomics, 86, 103094.
[26] Jordan, N. (1963). Allocation of functions between man and machines in automated systems. Journal of applied psychology, 47(3), 161.
[27] Kaber, D. B., Onal, E., & Endsley, M. R. (2000). Design of automation for telerobots and the effect on performance, operator situation awareness, and subjective workload. Human factors and ergonomics in manufacturing & service industries, 10(4), 409-430.
[28] Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness, and workload in a dynamic control task. Theoretical Issues in Ergonomics Science, 5(2), 113-153.
[29] Kendall, J. W. (1977). Variations of Delphi. Technological forecasting and social change, 11(1), 75-85
[30] Kotha, S., & Orne, D. (1989). Generic manufacturing strategies: a conceptual synthesis. Strategic management journal, 10(3), 211-231.
[31] Krogmann, U. (2000). From automation to autonomy-trends towards autonomous combat systems. Bodenseewerk Geraetetechnik GmbH (Germany FR).
[32] Legendre, P. (2010). Coefficient of concordance. Encyclopedia of research design, 1, 164-169.
[33] Lindstrom, V., & Winroth, M. (2010). Aligning manufacturing strategy and levels of automation: A case study. Journal of engineering and technology management, 27(3-4), 148-159.
[34] Lorenz, B., Di Nocera, F., Röttger, S., & Parasuraman, R. (2001, October). The effects of level of automation on the out-of-the-loop unfamiliarity in a complex dynamic fault-management task during simulated spaceflight operations. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 45, No. 2, pp. 44-48). Sage CA: Los Angeles, CA: SAGE Publications
[35] Malik, A. A. (2020). Robots and COVID-19: Challenges in integrating robots for collaborative automation. arxiv. org.
[36] Marsh, R. M., & Mannari, H. (1981). Technology and size as determinants of the organizational structure of Japanese factories. Administrative science quarterly, 33-57.
[37] Mital, A., & Pennathur, A. (2004). Advanced technologies and humans in manufacturing workplaces: an interdependent relationship. International journal of industrial ergonomics, 33(4), 295-313.
[38] MahmoudZadeh, S., Powers, D. M., & Zadeh, R. B. (2019). Introduction to autonomy and applications. In Autonomy and Unmanned Vehicles (pp. 1-15). Springer, Singapore.
[39] Mehta, A., & Subramanian, M. (2019). Investigating the barriers to increasing Levels of Automation.: A case study in pre-assembly of tap changer assembly line.
[40] Nagar, B., & Raj, T. (2013). An analytical case study of an advanced manufacturing system for evaluating the impact of human enablers on its performance. Journal of Advances in Management Research.
[41] Narula, S., Prakash, S., Dwivedy, M., Talwar, V., & Tiwari, S. P. (2020). Industry 4.0 adoption key factors: an empirical study on manufacturing industry. Journal of Advances in Management Research.
[42] Norwegian Forum for Autonomous Ships (NFAS): Definitions for Autonomous Merchant Ships (2017)
[43] Ntuen, C. A., & Park, E. H. (1988, October). Human factor issues in teleoperated systems. In Proceedings of the First International Conference on Ergonomics of Hybrid Automated Systems I (pp. 203-210). Elsevier Science Publishers BV.
[44] Ntuen, C. A., & Park, E. H. (Eds.). (2012). Human interaction with complex systems: conceptual principles and design practice (Vol. 372). Springer Science & Business Media.
[45] Ojha, R., Vij, A. K., & Vrat, P. (2014). Manufacturing excellence and its critical factors. Journal of Advances in Management Research.
[46] Riley, V. (1989, October). A general model of mixed-initiative human-machine systems. In Proceedings of the Human Factors Society Annual Meeting (Vol. 33, No. 2, pp. 124-128). Sage CA: Los Angeles, CA: SAGE Publications.
[47] Rouse, W. B., & Rouse, S. H. (1983). Analysis and classification of human error. IEEE Transactions on Systems, Man, and Cybernetics, (4), 539-549.
[48] SAE International: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles (2018)
[49] Salmi, A., David, P., Blanco, E., & Summers, J. (2015, October). Deciding the level of automation during the design of assembly systems: A literature review of decision methods and a new approach proposal.

[50] Sheridan, T. B., & Verplank, W. L. (1978). Human and computer control of undersea teleoperators. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab.
[51] Sheridan, T. B. (1980). Computer control and human alienation. Technology review, 83(1), 60-73.
[52] Sheridan, T. B. (1992). Telerobotics, automation, and human supervisory control. MIT press.
[53] Schmidt, R. C. (1997). Managing Delphi surveys using nonparametric statistical techniques. decision Sciences, 28(3), 763-774.
[54] Schneider, C., & Andersson, O. (2016). Examining Levels of Automation in the Wood Processing Industry-A case study.
[55] Singh, H., & Khamba, J. S. (2010). An empirical examination for enhancing the utilization level of advanced manufacturing technologies in India. Journal of Advances in Management Research.
[56] Stahre, J., Fasth, Å., (2010, June). Concept model towards optimizing Levels of Automation (LOA) in assembly systems. In Proceedings of the 3rd CIRP Conference on Assembly Technologies and Systems (pp. 1-3).
[57] Pathak, P., Singh, M. P., & Badhotiya, G. K. (2020). Performance obstacles in sustainable manufacturing–model building and validation. Journal of Advances in Management Research.
[58] Parasuraman, R. (2000). Designing automation for human use: empirical studies and quantitative models. Ergonomics, 43(7), 931-951.
[59] Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans, 30(3), 286-297.
[60] Proud, R. W., Hart, J. J., & Mrozinski, R. B. (2003). Methods for determining the level of autonomy to design into a human spaceflight vehicle: a function specific approach. NATIONAL AERONAUTICS AND SPACE ADMINISTRATION HOUSTON TX LYNDON B JOHNSON SPACE CENTER.
[61] Parasuraman, R., & Sheridan, T. B. (2005). Human-Automation Interaction. Reviews of Human Factors and Ergonomics, 89-129.
[62] Poornikoo, M., & Øvergård, K. I. (2022). Levels of automation in maritime autonomous surface ships (MASS): a fuzzy logic approach. Maritime Economics & Logistics, 1-24.
[63 (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? Applied ergonomics, 53, 190-202.
[64] Westin, C., Hilburn, B. and Borst, C. (2019). Mismatches between Automation and Human Strategies: An Investigation into Future Air Traffic Management (ATM) Decision Aiding. In Proceedings of the International Symposium on Aviation Psychology (ISAP) 2013 conference, Wright State University, Dayton, Ohio, USA (2013).
[65] Yadav, N., Mathiyazhagan, K., & Kumar, K. (2019). Application of Six Sigma to minimize the defects in glass manufacturing industry. Journal of Advances in Management Research.