A Case Study Initiating Discrete Event Simulation as a Tool for Decision Making in I4.0 Manufacturing

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Abstract. Smart manufacturing needs to handle increased uncertainty by becoming more responsive and more flexible to reconfigure. Advances in technology within industry 4.0 can provide acquisition of large amounts of data, to support decision making in manufacturing. Those possibilities have brought anew attention to the applicability of discrete event simulation for production flow modelling when moving towards design of logistics systems 4.0. This paper reports a study investigating challenges and opportunities for initiation of discrete event simulation, as a tool for decision making in the era of industry 4.0 manufacturing. The research has been approached through action research in combination with a real case study at a manufacturing company in the energy sector. The Covid-19 pandemic fated that adjusted and new ways of communication, collaboration, and data collection, in relation to the methods, had to be explored and tried. Throughout the study, production data, such as processing times, have been collected and analyzed for discrete event simulation modelling. The complexity of introducing discrete event simulation as a new tool for decision making is highlighted, where we emphasize the human knowledge and involvement yet necessary to understand and to draw conclusions from the data. The results also demonstrate that the data analysis has given valuable insights into production characteristics, that need addressing. Thus, revealing opportunities for how the initiative of introducing discrete event simulation as an anew tool in the wake of industry 4.0, can act as a catalyst for improved decision making in future manufacturing.

Keywords: Discrete Event Simulation · Decision support systems in manufacturing · Industry 4.0

1 Introduction

In the current era of Industry 4.0 (I4.0), the manufacturing industry is forming strategies for the application of new technologies towards increased digitization [1, 2]. There are several key technologies of I4.0 with relevance for the manufacturing sector i.e., the industrial Internet of Things (IoT), Cloud Computing, Big Data, Simulation, Augmented Reality, Additive Manufacturing, Horizontal and Vertical Systems Integration,

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Autonomous Robots and Cyber Security [3]. Among technological drivers for I4.0 are modeling and simulation-based development of productions systems [4], which can further their pertinency through technologies for real-time data collection and analysis to provide information to the manufacturing system [1, 5]. A field of knowledge that can contribute as a technological driver for I4.0 is Discrete Event Simulation (DES) [6]. In manufacturing settings DES has traditionally been applied to certain scenarios, such as identifying bottlenecks, experimenting with new factory layouts, and studying variations in the production flora [7, 8]. However, there is a potential for extended applications of DES as a tool for decision making in the era of I4.0. For example, automatic model generation and data exchange between manufacturing applications [9], coupling of modeling of production flows with multiagent-based simulation [10] and multi-objective optimization [11]. The advancement of real-time data acquisition has improved possibilities of such inputs into DES models [12]. Manufacturing today needs to handle heightened variability, uncertainty, and randomness, meaning smart factories need to become more responsive and faster to reconfigure [13]. Advancement of technologies can affect the application of production flow simulations, for example, easier and faster acquisition of large amounts of data for analysis to support decision making to deal with manufacturing variability and uncertainty. Hence, the possibilities of technologies within I4.0 have brought anew attention to the applicability of DES when moving towards design of logistics systems 4.0 [14]. Yet there exist barriers towards successful I4.0 implementation such as, insufficient digital skills and resources, ineffective change management, and lack of digital strategies [15]. There are theoretical discussions on how to move forward i.e. [16] suggest a stepwise implementation of the virtual factory in manufacturing. Further, [17] propose and show potential of a theoretical framework integrating artificial intelligence (AI), DES and database management technologies. Despite DES simulation being an established tool, the complexity of the modelling means that application of its full potential is still scarce, especially in small and medium-sized enterprises (SMEs) [18]. And there are unresolved issues when applying real-time simulation as short-term decision making [19]. Further, it is established that the process of building DES models is complex i.e., expensive, time consuming, and requires expertise [20, 21]. A considerable combination of quantitative and qualitative skills, large support from many areas of the organization, and extensive knowledge of tools and techniques are required when embarking on DES studies [22].

The outline above raises the possibilities of DES being a method benefiting from the increased emphasis on industrial digitalization and highlight challenges when aiming for DES to become a tool in daily planning of manufacturing and to facilitate the increased digitalized production. This paper reports on a real case study where a Swedish manufacturing company, jointly with a university, investigate the potential of implementation of DES in the company's manufacturing settings. The real case is part of a research project exploring the opportunities and challenges related to applications of simulation, data analysis, and artificial intelligence and human intelligence for future manufacturing.

The start of our study coincided with the first European wave of the Covid-19 pandemic, meaning that the planned activities for action research and case study had to be re-adjusted throughout the study. Thus, we also raise those aspects related to the Covid-19 pandemic in our real case.

The purpose of the study is to investigate the possibilities of applying DES as a tool for decision making in manufacturing to understand the prerequisites for succeeding on such a journey. The ambition is to enhance industrial knowledge of using DES when forming strategies for adoption of new technologies towards increased digitalization.

The research question asked is: *What are the challenges and opportunities for initiation of discrete event simulation as a tool for decision making in I4.0 manufacturing?*

In the following sections related work, concerning the possibilities and aspects of implementation of DES in manufacturing settings, is provided. Subsequently, the present real case is described, followed by findings, discussion, and conclusion.

2 Background and Related Work

This section outlines DES in its historic context and its current and future possible applications related to I4.0 are addressed.

Simulation is defined as an imitation of a system or a real-world process [23] and DES is the modeling of systems in which the state variables change only at discrete set of points in time and is especially useful when simulating systems with variability, interconnectedness, and complexity [21]. Traditionally DES in settings of manufacturing has been applied to study the impact of incorporating e.g., more variants into the production, determine the impact of new equipment or investigating bottleneck scenarios [7, 8]. Another common use is when building a new production facility to create a model on a high level to make a judgment of e.g., production capacity [9]. Further examples of using DES are when determining production planning policies [24, 25]. Meaning that DES is frequently used to support the production system design process for certain scenarios [26] and many applications have been reported in production plant design and in the evaluation of production policies, and planning [27]. The implementation of DES is a process that includes conceptual modelling, data collection and analysis, model coding, experimentation, verification, validation, and confidence [20, 21]. Data collection is often time consuming and there is the implication of availability of data, whether data needs collecting, or if data is not collectable [21]. There are crucial skills necessary when building DES models, such as programming skills, in combination with understanding logistical principles and moreover, awareness of the level of human involvement to determine what data, and how much, is needed for a given purpose [13]. To emphasis, there seems to be a potential of simplifying the process of implementing DES, for example the development of a framework for simulation model simplification, which aims to provide a unifying view, in terms of key activities and enabling and legitimatizing development of educational materials and their uptake [28].

As explained DES has been applied in certain manufacturing decision making, though in general its applications focus on investigating aspects of specific scenarios, often studied separately from daily planning, rather than being used continuously and strategically in long term decision making. Moreover, many companies may not have realized the potential benefits of DES and at the same time the method necessitates specific modelling expertise and requires extended communication between many functions at a company [22]. Further, the DES methodology requires extensive data collection, and lack of expertise not readily available in all businesses may mean that the threshold is too high to engage in implementation of DES. Thus, there may be a lack of understanding of the potentials of DES, especially among SMEs [18]. However, in the era of I4.0 the opportunities of DES have been raised anew as possibilities of real-time data collection, big data analytics coupled with machine learning and its application in short term planning are becoming more realistic [6, 9, 29]. Applications of real-time data driven DES models are becoming a possibility in the era of I4.0 [20, 30]. Implementation of real-time simulation strategies require agile simulation models and short computation times, nonetheless there are indications of the lack of such strategies [19]. The aspects of traditionally time-consuming data collection for DES modelling have the potential to improve in the wake of technologies for real-time data collection [3], though we are not quite there yet [13, 16]. Another aspect is the growing demand for real-time decision making, which evolves DES into a fundamental component of the digital twin, when 'sensing' shop floor data will become vastly available, execution of simulations provide almost real-time solutions enhancing performance of both manufacturing and logistics processes [14]. There is the potential of heightened capability for DES from applying big data analytics at stages of the DES methodology and use of DES in data farming to drive big data analytics techniques [31]. Though connecting DES to real-time data streams and big data sets requires further research [32]. Automatic generation of DES models is a future prospect, though requires further research [9, 33]. Techniques within artificial intelligence, such as applying machine learning [34] or agent-based modelling [35] for decision making can further add to the advancement of DES modelling.

We emphasis that manufacturing companies stress that simulation is an important part of I4.0 [4], indicating the increased interest of such applications in future decision making. However, combining DES with technologies in I4.0 for extended decision making is an area needing further and deeper investigation to reach its potential [9, 13, 16, 32]. It is therefore of interest to explore the challenges and opportunities for DES as a sustainable activity for decision making in increasingly digitalized manufacturing. Meaning there is a need in a manufacturing industry characterized by variability and uncertainty to make the most of I4.0 technologies and find novel ways to support decision making of production planning.

3 Method and Approach

This research has been approached through action research in combination with a real case study. The method of action research *"is driven by a desire to bring about change in practice and it strives toward a form of action in order to identify and solve problems"* [36]. Further, action research is characterized by collaboration between researchers and participants from the setting, where they jointly study and derive solutions to a problem [37]. The research focuses on a real case study, where a researcher and third year bachelor students from a university collaborate with participants from a manufacturing company, to investigate the potential use of DES in production planning decision making. The method of action research, as a bridge between academic research and practical work, focus on practice, change, collaboration, and action [36] and is therefore a suitable approach to investigate the case at hand. Case studies can be exploratory and are suitable when more in-depth knowledge concerning an event is sought-after [36] and when the emphasis is on intensive examination of the setting [37]. The choice of approach and the combination of methods were based on the aspects of close involvement between different actors to jointly investigate the real case to develop and suggest solutions. However, the start of the study coincided with the start of the first European wave of the Covid-19 pandemic. This meant that the planned project and previously experienced models for action research of similar cases had to be re-adjusted throughout the study. Under regular circumstances frequent visits with substantial time spent at the factory site by the university researcher and the bachelor students would have taken place. It is common, in Sweden, for engineering students to mainly be based at the company during their thesis work. As visits to the factory site were strictly regulated because of the Covid-19 pandemic it was only possible for the bachelor students to pay one visit to the company very early on and the researcher could not make any visits to the company. Nor could the researcher, who was supervising the students, meet physically with the students at any time. Those implications meant that new ways of communicating had to be applied. Also, the aspect of understanding a manufacturing facility, with all its processes and production flows, at a distance through mainly studying spread sheets had to be overcome. Nevertheless, throughout the case study, both quantitative and qualitative data were collected from the manufacturing processes at the company. The production data was retrieved from the company Enterprise Resource Planning (ERP) system by the participating project group member from the company. The quantitative data collected was shared via e-mail in the format of Excel files. The qualitative data consisted of meeting notes with company employees to understand the manufacturing layout and processes, and the organization of the company. Regular weekly web-based meetings took place between the three parties, company participant, researcher, and bachelor students. Those meetings were of great importance to understand the manufacturing process and to jointly analyze the data. The qualitative data collection took place in the span between March-June (four months) 2020. The quantitative data collection incorporated data, such as processing times from the manufacturing, which then was analyzed in preparation for building a DES model of the factory shop floor. While the quantitative data was collected during same time period as the qualitative data, the actual data from the quantitative part historically spans over a period of 13,5 months between autumn 2018 until autumn 2019. The collected data was analyzed according to data formats necessary to design and build the DES model.

4 Case Description

The real case is based at a company that manufactures products for the energy sector. There is an interest among middle management to investigate the potential of DES, both to evaluate different production scenarios, but also to explore the potential of this approach becoming a sustainable day-to-day planning activity. No expertise within the area of DES exists at the company, hence the project group is brought together with a researcher from the collaborating university and two third year bachelor students in industrial engineering as part of their final year thesis work. The students have studied courses within logistics and lean manufacturing, though lacks thorough expertise in DES modelling. Hence, they were given access to an online university course on DES when commencing the project. The representative from the company, in the project group, had a positive view of the potential of this method and was engaged throughout the case study and was also the person retrieving the production data from the Enterprise Resource Planning (ERP) system. This proved to be especially vital in this case as the Covid-19 pandemic strongly impacted the communication between project group members. The company has been fairly spared from the Covid-19 pandemic regarding the aspects of not needing to lay off or furlough employees. However, due to the pandemic, the collaboration between the researcher, students, and the company personal was largely affected. It was only possible to visit to the factory site once, very early on, thereafter all other communication took place through web-meetings, e-mails and sharing of Excel-files with production data.

To limit the extent of the data collection for this specific case and to give the company the chance to begin applying DES in a grasping format we jointly identified to focus the study on the company's two highest volume product variants. This limited the scope of the case study, but also gave a base of including substantial data collection for high volume products that passes through many of the different processes on the factory shop floor. The manufacturing processes consist of some CNC-machines and automation equipment, though many processes, for example, within welding are manual. The factory layout is a so-called job shop, meaning that similar equipment or functions are grouped together, such as welding processes located in one area and grinding machines in another. The studied production flows of the two product variants share many resources, though they are routed differently throughout the shop floor. Product variant 1 has 15 operations and Product variant 2 has 19 operations. The production flows are disparate, and some resources are visited several times. The data collection included processing times (planned and reported times), waiting times, repair times (extra operations) and times for sending products on sub-contraction. The data needed thorough categorizing and processing to be analyzed in a suitable format i.e., calculating waiting times and deducting number of repair operations from the data files. The data analysis was time consuming and the group members jointly discussed and categorized the production data, to reach consensus of the interpretation of the data.

5 Results, Analysis and Discussion

This section outlines the findings of the real case study over three aspects; the result of the analyses of the data for building a DES model, results on applying action research and real case study during the Covid-19 pandemic, and the results and learnings made from this real case on how to move forward with DES as regards challenges and opportunities of introducing DES as a tool for decision making in future manufacturing.

5.1 Results from Data Collection Analysis of the Production Data

Based on the data collection, the total production times from starting a new order until the order being completed were calculated. Data was collected to investigate possible discrepancies between planned processing times (retrieved from the ERP system) and reported processing times (reported by operators after completions of operations). Further, from the data we could obtain the number of extra operations (repairs), waiting times between the different operations and variation in sub-contracting times. To clarify the results of the calculations, tables and graphs were drawn for the various aspects studied as outlined above. The Tecnomatix Plant Simulation software [38] was used to model and visualize the production flow according to product routing of the two variants. The production flows are complex with several loops and crossing flows between the two production variants, therefore a simplified DES model was built as part of the case study. Further work and extension of this model is ongoing.

When initiating the study, the company proposed that there might be large discrepancies between the planned and the reported processing times. Though, the study showed that the total discrepancies between planned and reported processing times did not vary as much as anticipated. There was on average only a slight increase in the reported processing times compared to the planned times, and overall the data set followed the same pattern. It should be noted that the planned processing times are set by a production engineer according to a pattern, whereas the reported data is given by the operators themselves after completion of an operation, meaning the reported data may be less reliable, as it is subject to human interaction and judgement.

The company was aware of long waiting times between operations and products are frequently sent to storage in waiting for the next operation. Therefore, there was an interest to study those implications in more detail. The study confirmed a high level of work-in-progress and the extent of the waiting times were quantified, showing the importance of addressing those issues at the case study company.

Early in the production flow the products are sent to a sub-contractor for processing that cannot be performed in-house. Notable the processing times for sub-contracting varied substantially and demonstrated a trend showing how the sub-contracting times increased over the data set studied. Here improved communication with sub-contractors would be beneficial to find causes for this and break the trend of increasing times.

The data analysis showed that for the first product variant studied, 86% of the orders required at least one, but often several repair operations and for the second product variant studied, 43% of orders needed repair operations. The results from the study of repair times indicate that there are quality issues that need further investigation and can be the basis for reformed decision making. Moreover, the added repair operations to the production flow meant that the total processing times increase compared to the originally planned times that initially do not consider or plan for repair cycles. The added repair operations entail an almost constant re-flow of products that revisit operations, making the production flows increasingly complex to analyze and model.

The calculations of the total production times from starting a new order until the order being completed, demonstrated a trend in the data where there is a near 50% increase in total production times, for both product variants, throughout the data sets (see Fig. 1). Due to confidentiality and to avoid disclosure of detailed company data, Fig. 1 does not include the specific production times and unit, though it shall be stressed that the graph displays the result of the analysis of the real production data.

Speculating on the reasons for the increase in production times it can be highlighted that the long waiting times, many repair cycles, and increasingly longer sub-contracting

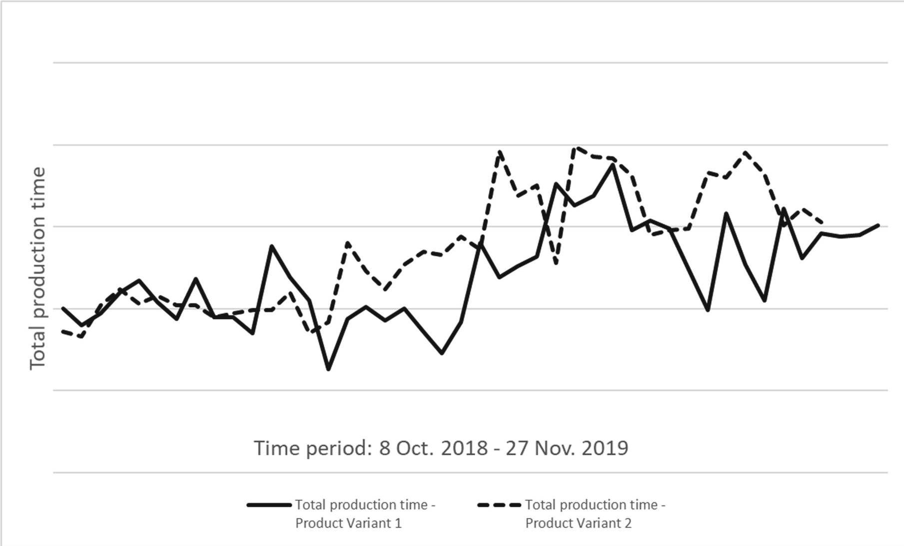

Fig. 1. Total production times for Product Variant 1 and Product Variant 2, respectively.

times have an impact on the total production times. However, the ground reasons why those changes in the data takes place need further investigation as to understand why this is happening and to come to terms with those issues and improve the production flow. The detailed study of the production data showed demonstrated results that need further addressing. In autumn of 2020 the researcher and company representative reached involvement of company management, who showed interest in the results and emphasized importance of continued study. Therefore, the results are now the basis for further investigation leading to future changes in decision making in the real setting.

5.2 Applying Action Research and Case Study During the Covid-19 Pandemic

The study was planned in the months before the first wave of the Covid-19 pandemic hit Europe and when the project started in March 2020 the pandemic was rising fast. Our chosen methods of action research coupled with a real case study therefore quickly needed to be re-adjusted and different ways of communicating, collaborating, and collecting data had to be explored. We had planned frequent visits to spend time at the company to observe and learn the manufacturing processes, collect data, and interview operators on the shop floor. And the most apparent impact on the study was that this was limited to only one visit made by the bachelor students and none by the researcher. Instead, the progression to understand the manufacturing processes and the company problems took place through web-based meetings. During the web-based meetings the company participants explained the manufacturing processes in detail and jointly we extensively studied and analyzed the data files to understand the production flows e.g., times, order of processes, type of equipment, and human resources. This distant way of learning the manufacturing setting was time consuming, repetition was constantly necessary, and it probably took longer to get a full picture and a clear grip of the manufacturing issues. This made the study initially somewhat abstract, and the restrictions to visit the company site meant that the study did not give possibilities for interviewing company personnel. More interactions with operators, logistic planners, quality engineers etc., would probably have benefited the understanding of the manufacturing and i.e., reliability of the data regarding reported processing times could have been further investigated.

Another aspect of not being able to meet was the student supervision. It was difficult to give hands on advice on DES modelling, as this was done through web-based meetings. It also took time for the students to get access to the Tecnomatix Plant Simulation software [38], as licenses were limited to computers in physical classrooms at the university. This was eventually solved by a new system of login through a distance computer solution. The students were given online course materials (films, lectures, exercises booklet) to learn the software, but progress was slow, and they would most likely have progressed faster with more teaching interactions.

The changed ways of communications and adjusted form of collecting data resulted in researcher and students main form of communication with the company being through web-based meetings and e-mail conversations with one company participant. And this in turn made it difficult to disseminate the result of the study at the company as many people were not even aware of the study and meanwhile management were informed there were no clear communication routes or initial interest of the study. Though, in autumn of 2020 the researcher and the company representative found interest from the company management team, meaning the subsequent continuation of the initiative. Management shows a large interest in continuing the work on several levels, both with extended DES models, incorporating more product variants and in parallel to work with improvement of quality issues and enhanced communication with sub-contractors.

The summarized findings from this section highlights the importance of human interaction to interpret, explain and analyze the data, as well as when learning novel software and engaging the interest of management.

5.3 Challenges and Opportunities on a DES Journey Towards I4.0 Manufacturing

As demonstrated the initiation of the DES study and the data collection part have given valuable insights in the details of the production. Moreover, throughout this study, there are lessons learned on a more tacit level related to aspects of introducing DES as a tool for decision making for future manufacturing.

During the data collection we note that manual and human work was required, both for retrieving the data and for the analysis. The data was available in the company's ERP system, though it had to be manually retracted and transferred into Excel files. Data collection and analysis are often described as time consuming, where necessary data is not readily available for collection [21]. Our real case demonstrates and confirms those principles as the data collection and analysis were substantial parts. In this case it can therefore be argued that in real factory settings, data readily available for automatic analysis is yet to become a realistic scenario. Thus, we note the continued interpretation of the data facilitated through human knowledge when collecting, categorizing, analyzing and understanding the data. This interaction with humans in the system also meant that it was difficult to keep a neutral judgement of to the study as preconceptions of anticipated results were raised before and throughout the study. Some of the preconceptions were disproved when analyzing the data, showing how such influence can affect the mindsets of humans. This argues for further possibilities of data collection and analysis with less human interaction in future decision making.

It is known that a range of different competences and specific expertise is necessary when embarking on a DES study [22]. In the real case study presented there was a low knowledge of application of the DES method within the company and the method was newly introduced also to the bachelor students, which emphasized and confirmed the long learning curve to encompass all necessary abilities, i.e., technical, theoretical, quantitative, and qualitative aspects of such a study.

Despite the challenges encountered, the results of the case study demonstrate new knowledge of the production processes that can be brought to light in decision making. The new understanding of the production data is the basis for further studies regarding i.e., improvements of production times, work-in-progress, and highlighting of quality issues. Particularly as the collaborating company is keen to continue with the DES approach to study how production output is affected by the discrepancies in processing and throughput times. Economical key performance indicators related to the aspects of capital bound in work-in-progress is also an aspect the company has highlighted. The study showed the company's immaturity to apply DES and their lack of production data in readily formats for modelling. At the same time the study demonstrated the potential of commencing a DES journey as the results highlight possibilities for improvements of production.

6 Conclusion

The real case outlined in this paper focuses the challenges, yet opportunities for implementation of DES as a tool for decision making in increasingly digital manufacturing. Our results show that the commencement of a DES study, which involves detailed data collection and thorough understanding and analysis of the data, can concretely give input to areas within production that need addressing and require further investigation. This implicates the possibility for revised decision making to improve production times and flows and hence influence production efficiency and improve competitiveness and responding faster to changing markets.

We encountered a variety of challenges during the study. The challenges include the added aspect of performing action research and real case study in midst of the Covid-19 pandemic, the impact from the low level of expertise within the technical aspect of DES modelling, the time-consuming period of data collection and analysis and the necessity of human knowledge and interaction during this process. The emphasis is that it is still vital with human input when understanding and drawing conclusions from data to be the basis for decision making. At the same time, we reflect on the implication that human preconceptions may have on the results, denoting that the data analysis and DES model can be valuable when striving towards objectivity. Consequently, the initiation of the DES approach has increased the understanding of the complexity of the production flows and has endorsed a more holistic view of the factory environment.

Despite the challenges outlined, the results from the real case study have proven a useful insight for the company regarding the outcome of the analysis of production data. The results from the data analysis have been presented and highlighted to the company management team. This in turn has facilitated discussions between managers on how to move forward with fresh studies of production and how to continue with the incentive of implementing DES aiming for improved decision making.

The Covid-19 pandemic meant that adjusted and new ways of communication, collaboration, and data collection were explored and tried. The limitations of communication made it more difficult to disseminate the result of the study at the company and keep management informed. The commencement of a DES journey has demonstrated how the method can act as a catalyst for addressing improvements of production that can lead to more accurate decisions and increase production efficiency. We realize the need for future studies of this area, emphasizing the applicability of DES as tool for decision making and the ambition to enhance industrial knowledge of its possibilities within the era of increased digitalization. We also recognize the importance of human interaction and critical thinking leading Industry 4.0 into Industry 5.0 [39] as our results emphasize human interaction and interpretation throughout the study.

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