A Data Mining application to quality control: a case study in the fashion industry

Fani V.*, Antomarioni S.**, Bindi B.*, Bandinelli R.*, Ciarapica F.E.** and Bevilacqua M.**

** Dipartimento di Ingegneria Industriale, Università degli Studi di Firenze Viale Morgagni 40/44, 50134 – Firenze – Italy (virginia.fani@unifi.it, romeo.bandinelli@unifi.it; bianca.bindi@unifi.it)*

*** Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Via Brecce Bianche 12, 60131 – Ancona – Italy (s.antomarioni@univipm.it; f.e.ciarapica@staff.univpm.it; m.bevilacqua@univpm.it)*

Abstract: Nowadays, quality issues represent one of the most time-consuming activities that companies have to manage and they are becoming even more relevant than in the past due to the increased attention paid to reducing lead time to reach the requested service level. Even though high-quality standards can be targeted with 100% control on the produced items, it will require non-competitive time to deliver final products. Statistical analysis requires skilled resources to practically guide companies in the identification of sampling rules specific for a single item or item category as well as related to different materials in order to carry out targeted controls. In addition, easy-to-update datasets and rules are needed in the current dynamic contexts, discouraging statistical analysis that even requires skilled resources. Data mining techniques can be leveraged to analyse large amounts of data efficiently and effectively, preferring methodologies that intuitively provide results even for the non-experts in the analytics domain. According to this, a data-driven approach based on data mining could support companies in setting the sampling rules that better fit the items to be produced, in order to optimize the trade-off between the targeted compliance and the time to check it. Finally, a case study will demonstrate how the proposed approach suits dynamic and low-tech industries like the fashion one. A step-by-step implementation of the proposed procedure based on Association Rule Mining, indeed, has been perceived by the final users as both intuitive and meaningful, supporting them in discovering non-trivial relationships between data.

Keywords: "Data mining", "Case study", "Quality Control Management", "Sampling rules", "Fashion industry"

I. Introduction

Nowadays, an even larger number of companies are implementing Industry 4.0 (I4.0) tools to collect vast amounts of data related to different areas, from product and process design to production and quality control. Fault detection and defect prediction represent one of the main critical areas to manage, especially because they are time-consuming activities with a high impact on lead time. On the other hand, they are necessary to guarantee the outstanding quality level that final consumers require. The trade-off between increasing quality controls to intercept product defects and decreasing them to reduce the delivery time represents a competitive challenge, especially for dynamic contexts where the aesthetic of the product is central, as the fashion one.

Even low-tech industries are implementing I4.0 solutions to track huge amounts of data related to outcomes of quality controls and detected defects, but the use of collected data has been limited, leading to the "rich data but poor information" problem [1]. The need for intelligent and automated data analysis tools to extrapolate useful knowledge from data is, therefore, crucial to gain competitive advantages in the market and manage the trade-off described above.

Easy-to-update datasets and rules are needed in the current dynamic contexts, discouraging statistical analysis that even requires skilled resources. Data mining has emerged as an important technique for knowledge acquisition from manufacturing databases, applied to search for hidden relationships which can be used to support decision-makers [1]. For instance, historical data related to outcomes of quality controls could give feedback about how the adopted sampling rules perform, suggesting if the sampling percentage is too low or high: in the first case, a higher sampling percentage should be chosen to intercept non-compliances at the first control round; in the second case, a lower sampling percentage will allow to guarantee the same quality level in a shorter time. The sampling percentage should be defined at the supplier level just in case all the managed products are comparable in terms of defect occurrence. Suppliers who manage different dimensions, such as product categories (e.g., shoes, bags), materials (e.g., leather, cotton) or production phases (e.g., cutting, assembly), should identify sampling rules specific for a single item or item dimension in order to carry out targeted controls.

A data-driven approach based on data mining has therefore been proposed to support companies in setting the sampling rules that better fit with each supplier and the items to be produced, in order to optimize the trade-off between the targeted compliance and the time to check it. Indeed, since a data-driven approach allows the dataset to be updated in a streamlined manner, the risk of basing sampling size definition on out-to-date information is avoided. On the other hand, only the necessary quality control will be carried out according to the performance trend of each supplier. A case study in the fashion industry will demonstrate how the proposed approach suits dynamic and low-tech industries. Among data mining techniques, Association Rule Mining (ARM) has been chosen due to their easiness-to-use, representing an intuitive method for discovering relevant relations between variables in large databases with no need to make hypotheses before. This aspect represents a large benefit brought by the method since it allows to explore data in any direction and capitalize on all the information derived from them, without being obliged to define research directions a-priori. Results interpretation is instantaneous even for non-domain experts thanks to their representation [2]. The application areas in which ARM can be implemented are wide, including the quality management field; however, its application to the quality management in the fashion industry is more limited and should be extended, as observed by [3].

The article has been structured as follows: in section 2, we investigate the industrial and scientific background; in section 3 the proposed data-driven approach has been detailed; in section 4, the results carried out with the case study have been shown; finally, section 5 sums up conclusions and further developments.

II. INDUSTRIAL AND SCIENTIFIC BACKGROUND

In the current industrial scenario, international standards are being used to support the definition of quality control plans and processes. For example, UNI ISO 2859-1:2007 standard supports the sampling system for acceptance of goods received from suppliers, which is based on the acceptable quality level (AQL) of the batch received. The objective of this kind of control is to induce the supplier to maintain an average quality level of the supply process not lower than the specified acceptable quality limit while ensuring the customer an upper limit for the risk of occasionally accepting a poor quality lot [4]

Several authors have pointed out that basing the quality control process only on the standards leads to the adoption of static parameters and, therefore, they are rarely adapted to the fast-changing characteristics of the industrial environment [5]. According to Rivera-Gomez [6] companies should also take into consideration other aspects, like the economic one and the interaction with production and maintenance management, basing on dynamic sampling strategies. Similarly, Hajej et al. [7] developed a dynamic sampling process, also accounting for failure and production rates related to the degradation of the machinery. In Samohyl's [8] perspective, hypothesis testing and specific statistical distributions can be applied to ensure an effective sampling strategy both for producers and consumers.

Considering the application to the fashion industry, which is a low-tech and dynamic sector mainly characterized by manual operations rather than automated processes [9], previously mentioned techniques may result complex to implement. The need for an automated and data-driven analysis suggests the adoption of data mining approaches [10]. Indeed, data mining applications to support quality management can be found in existing literature: for example, Ur-Rahman and Harding [11] pointed out how identifying contributing parameters from large datasets has a positive impact on the improvement of product quality. Consequently, data mining techniques and tools can be considered facilitators of quality prediction allowing hidden knowledge extraction [12]. Among the other techniques, association rule mining is a useful approach that can be applied to identify hidden relationships between events or conditions that occur together [13]. Their application to the quality management field is not novel: for instance, Da Cunha et al. [14] applied the association rule mining to analyze and improve assembly operations, identifying sequences leading to faults and, thus, defining appropriate strategies to avoid them. Instead, Buddhakulsomsiri et al. [15] used it for the root cause analysis of warranty problems in the automotive field. More recently, ARM has been applied to relate components frequently failing together in order to define appropriate maintenance strategies [16]. However, ARM application to the fashion industry is more limited: as suggested by Yildirim et al. [3], relationships among fabric parameters in textile data could be extracted to describe common characteristics leading to defects or high-quality products. Lee et al. [17] instead, mined association rules to relate production process parameters and product quality in the garment industry. Similarly, Lee et al. [18] proposed a quality management improvement plan in the same sector basing on the defects identified during the final control of the garment produced: in this way, the defects concurrently identified through the association rules served as a roadmap to avoid them.

Despite the valuable applications of association rule mining approaches in the literature, they have not yet been applied to improve the sampling process. Hence, in the proposed application, ARM will be used to determine the sampling rules that better fit with each supplier and the items to be produced, in order to define a trade-off between batch compliance and control duration.

III. RESEARCH APPROACH

The application of data mining techniques can provide valid support for the decision-making regarding quality control policies since they enable to simultaneously take into consideration several attributes in the dataset. Moreover, they can be integrated into the company's current operational processes, with the aim of improving the current state of the activity without disrupting it. In this context, this paper proposes an approach aiming at improving quality control process, by adapting the sample size on the bases of suppliers’ performance and attitudes.

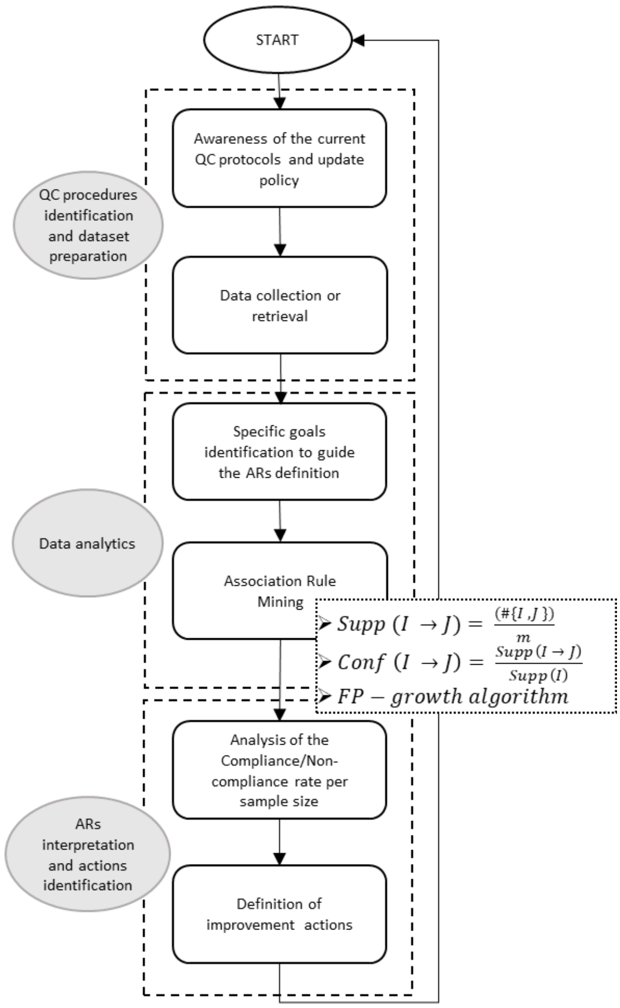

Fig. 1 Research approach schematisation

The main steps of the procedure, represented in Fig. 1, can be summarized as follows:

I. *Quality Control (QC) procedures identification and dataset preparation*: in order to ensure an efficient analysis of quality control processes, it is necessary to be aware of the QC protocols currently applied by the company and, possibly, how often they are updated and according to which principles. It is also necessary to rely on reliable and accurately populated datasets. In this sense, information on previous control outcomes, sample size, and policies in case of non-compliancy is needed for all the suppliers and for all the products and has to be collected or retrieved by existing information systems.

II. *Data analytics*: once the dataset has been prepared and validated, the analytics can be performed by mining the association rules. Specifically, the ARM involves the identification of couples of conditions that co-occur frequently. Specific goals can be set for the analysis and the Association Rules (ARs), depending on the attributes in the dataset and on the available information. For example, the focus can be centred on identifying the compliance rate of a supplier considering the associated sample size and, possibly, detailing this value per article material or product category. The results obtained ad this step, namely the ARs, will be used to re-arrange the quality control process, e.g., the sample size. As already mentioned, ARM will be applied to determine the association.

Hereinafter, a brief formalization of this technique is provided [15]: let A = {a1, a2,..., an} be a set of items (i.e., Boolean data) and V = {v1, v2, …, vm} be a set of transactions, each of whom is composed of an itemset (i.e., a set of items) taken from A. The implication between two itemsets belonging to A is an Association Rule: I→J, where I, J ⊆ A and I ∩ J = ∅. Several metrics can be used to measure the quality of an AR. In this work, the support (Supp) and confidence (Conf) are recalled:

a. The support of rule I→J can be computed as the probability of finding both I and J in a transaction; it can also be seen as a joint probability, i.e., the number of transactions both containing the itemsets I and J over the cardinality of the transaction set. $Supp\ (I \rightarrow J) = \frac{(\#\{I,J\})}{m}$.

b. The confidence of rule I→J is calculated as the conditional probability of having item J in a transaction already containing I (P(J | I)). $Conf\ (I \rightarrow J) = \frac{Supp(I \rightarrow J)}{Supp(I)}$

In this work, FP-Growth algorithm [19] is used to mine the ARs.

III. *ARs interpretation and actions identification:* once the ARs have been extracted, their interpretation is necessary to make a data-driven decision. Specifically, each supplier can be evaluated by comparing the compliance/non-compliance rates and the associated sample size. For example, if a supplier is reliable in terms of quality assurance but is controlled on large sample size, then such percentage can be reduced. Additionally, different sample sizes can be adopted depending on the product category or the specific article material, if the compliance rate of a supplier varies with these attributes.

IV. Results

The proposed data-driven approach has been implemented in a fashion company to demonstrate its applicability in real contexts. The involved company is a French luxury brand that currently markets a wide range of products, from leather goods, shoes, ready-to-wear products, and jewellery, as well as fragrances owned by licensees. Leather goods market segment will be the object of the case study, according to the company's suggestions. The leather goods division located in Tuscany managed a huge amount of data related to quality controls on final products made by suppliers. The main criticalities the company refers to the analysis and elaboration of the collected data in order to answer a twofold question: on the one hand, to understand if the sample size identify for the quality controls per supplier is adequate; on the other hand, to identify, if any, product features that could positively or negatively influence the outcome of quality controls, requiring a targeted definition of sample size not only per supplier but even per product feature. Currently, indeed, the company usually defines a single sample size per supplier, independent of product features such as the main material and the product category. With no data analysis, the company can not be confident that the used sampling rules are correctly defined or have no need to be updated according to recent data or segmented according to product features as described above.

The proposed data-driven approach has been applied starting from the company dataset that includes the one-year outcomes of quality controls made on final products at the end of the production process, basing on more than 50,000 records. The dataset structure is shown in Table I.

TABLE I
DATASET STRUCTURE

Dataset column	Data type	Example
Order year	Int	2021
Order number	Int	1
Order row	Int	1
Control lot	String	ABCD-2020-1234-A
Serial number	Int	5352690000005213
Supplier code	Int	1
Product category	String	Bags
Article style	Int	1233456
Article material	String	1
Article colour	Number	1000
Article size	String	U
Quantity ordered	Int	24
Quantity controlled	Int	8
Sample size	Int	30
Control round	Int	1
Outcome	String	To be re-checked

The single item is univocally identified by the RFID tag (i.e., "Serial number" column in Table) and belong to the order row referenced by the dataset columns "Order year", "Order number" and "Order row". Order rows refer to a single article type, identified according to four dimensions, for instance, the product shape, material, colour and size (i.e., "Article style", "Article material", "Article colour" and "Article size" respectively in Table), and belonged to a product category (i.e., "Product category" in Table). More than 700 material codes are managed by the company and 4 product categories are used in the leather goods division (i.e., bags, belts, luggage, and small leather goods).

Each order is assigned to a supplier (i.e., "Supplier code" in Table) and sampling rules per "Control round" are currently defined by the company as a fixed percentage (i.e., "Sample size" in Table) of ordered quantity (i.e., "Quantity ordered" in Table) per supplier. The resulting controlled quantity (i.e., "Quantity controlled" in Table) count the items of the order to be controlled that will be identified by a specific "Control lot". At the end of each control round, the outcome has been registered (i.e., "Outcome" in Table).

The 2-rounds quality control process managed by the company is represented by the schema in Fig. 2**Errore. L'origine riferimento non è stata trovata.**. Once the supplier declares to be ready for the inspection, an appointment is arranged with the brand owner to engage the quality supervisor to perform the on-site control. During the first round of checks, the compliant and non-compliant items have been identified, considering the number of pieces to be controlled and the tolerance thresholds defined per supplier. While the compliant items can be delivered to the brand site, the others are directly sent back to the supplier for repairing only in case they are not urgent. On the other hand, orders to be quickly processed that do not exceed the minimum tolerance threshold for the controlled items will require the 100% control of the production lot which could consequently result in a positive or negative final outcome (i.e., the order is delivered or returns to supplier respectively). The 2-rounds of quality controls could be therefore carried out only for urgent work orders that need to be immediately processed: the first round of checks, based on the sampling rules defined per supplier, could result in "Compliant", "Non-compliant" or "To be re-checked" outcomes; the second round of controls, made only for "To be re-checked" production lots which are the urgent work orders that did not successfully pass the first round of check, extend the number of controlled item to 100% of the lot and could result in "Compliant" or "Non-compliant" outcomes.

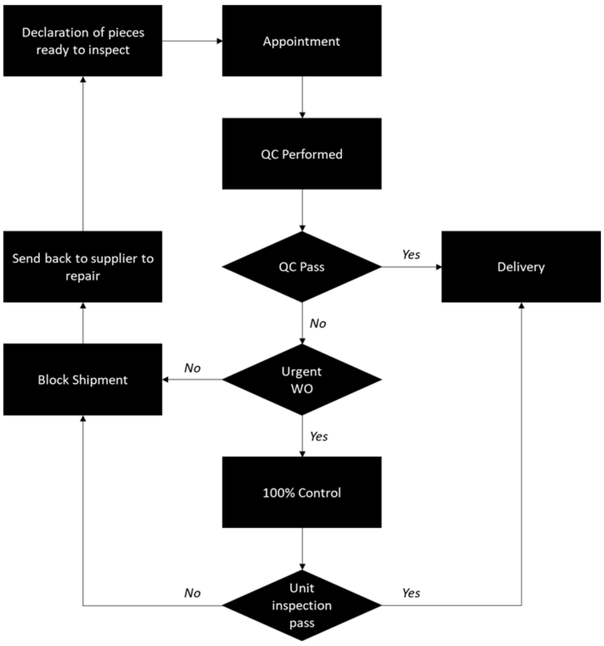

Fig. 2 Quality control process for the analysed company

* QC = Quality Control, ** WO = Work Order

The sampling rules defined per supplier can be equal to 15% or 30% for the first round of controls, while for the second one, if any, is 100% for all suppliers. "Non-compliant" lots will be sent back to suppliers for their reconditioning. A sample size equal to 100% at the first round is used for all suppliers only for valuable items. Table II shows the sampling rules defined by the company for its 39 suppliers, made according to the type and duration of the supply agreement, and never updated. Information on the suppliers' identity and on article materials have been codified in order to respect the privacy policy required by the company.

TABLE II
SAMPLING RULES PER SUPPLIER (1ST ROUND OF QUALITY CHECK)

Supplier code	1st round quality check
2, 6, 7, 11, 14, 15, 24, 25, 31, 39	15%
1,3, 4, 5, 8, 9, 10, 12, 13, 16, 17, 18, 19, 20, 21, 22, 23, 26, 27, 28, 29, 30, 32, 33, 34, 35, 36, 37, 38	30%

Considering this information on the company and the structure of the dataset reported in Table I as a starting point, the association rule can be mined. For the proposed case study, a step-by-step procedure is presented to identify whether and how to modify the sampling policies for the various suppliers. After a discussion with the quality management team of the company, the following ARs have been analysed focusing on the first round of quality checks:

1. *Supplier code, Sample size → Outcome*: this rule allows to identify whether the supplier is able to provide compliance lots only by considering the associated sample size. If the confidence of the rule relating supplier code, sample size, and a compliant outcome is 100%, there is no need to proceed further. However, it should be discussed whether a lower sample size can be associated with the supplier in order to hasten the quality check. Otherwise, it is worth understanding if the performance of the supplier depends on other attributes.

2. *Supplier code, Sample size, Product category → Outcome*: this rule allows to identify whether the product category has an impact on the outcome of the control, since the expertise of a supplier can be stronger in the manufacture of a product category. Even in this case, if the confidence of the rule relating supplier code, sample size, product category, and a compliant outcome is 100%, there is no need to detail the analysis further.

3. *Supplier code, Sample size, Product category, Article material → Outcome*: the analysis of the correctness or efficacy of the sampling size is related to the specific material, as the company suggested (i.e., some recurrent non-compliance can be related to the nature of the main material of which the product is composed).

In this perspective, let us consider the ARs related to supplier 7. The first group of rules, reported in Table III, shows that three different sample sizes are applied for supplier 7. Considering the sample size of 100%, according to the confidence (Conf = 1.000), the supplier always presents reliable outcomes. According to the statement made at point 1), there is no need to deepen the analysis through the ARM in this direction. This virtuous supplier behavior could be rewarded with incentives to support successful results (e.g., production bonuses) and, at the same time, would lead to the idea of reducing the sampled percentages, so as to shorten the time spent on quality control. In general, lots sampled, for example, at 30% could be sampled at 15%; in the specific case, lots sampled at 100% represent products of particularly high value (i.e., valuable) and, therefore, a reduction in sample size is undesirable since a defect in these products would cause high costs, both economically and in terms of image.

TABLE III
ASSOCIATION RULES RELATING SUPPLIER CODE, SAMPLE SIZE → OUTCOME

X	Y	Supp	Conf
Supplier code = 7, Sample size = 15%	Outcome = Compliant	0.004	0.941
Supplier code = 7, Sample size = 100%	Outcome = Compliant	<0.001	1.000

Conversely, when the sample size is 15%, the final outcome is "Compliant" in 94.1% of cases (Conf = 0.941). According to the procedure provided, the ARs detailing the performance of the supplier in terms of product category should be mined in order to assess whether some product category is more critical than others. As reported in Table IV, two different product categories are associated with a sample size of 15%, i.e., bags and small leather goods. The former results in being compliant in 93.2% of cases, while the latter in 96.0%: it can be said that there is no substantial imbalance to suggest focusing on one category over another: therefore, further discussion of the rules by material will be given in both cases.

TABLE IV
ASSOCIATION RULES RELATING SUPPLIER CODE, SAMPLE SIZE, PRODUCT CATEGORY → OUTCOME

X	Y	Supp	Conf
Supplier code = 7, Sample size = 15%, Product category = Bags	Outcome = Compliant	0.003	0.932
Supplier code = 7, Sample size = 15%,	Outcome = Compliant	0.002	0.960

Product category = Small Leather Goods

In Table , the ARs involving the article materials needing a more accurate check are listed. Specifically, in the case of material 661, the Conf = 0.454 indicates that in 45.4% of cases such product will need to be rechecked. This indicates that the 15% sample does not meet an adequate quality level and that the lot needs to be delivered urgently. Materials 118 and 475 are "Non-compliant" respectively in 14.3% and 25.0% of cases. They can be sent back to the supplier for reconditioning since they do not appear to be urgent. In all these cases, some measures in the quality control policy are important, as well as understanding the nature of the defects that lead to the rejection of the batch. Given the reliability of the supplier with regard to the others, one might consider increasing the sample sizes analyzed for these article materials. The further control foreseen by the current company policy would require to go from 15% to 100%. In this case, if acceptable quality levels are found, intermediate steps could be envisaged, such as 30% or 50%. In this way, there would still be more monitoring of the batch, but without particularly burdening the duration of the quality control process.

TABLE V
ASSOCIATION RULES RELATING SUPPLIER CODE, SAMPLE SIZE, PRODUCT CATEGORY, ARTICLE MATERIAL → OUTCOME

X	Y	Supp	Conf
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 118	Outcome = Non-compliant	<0.001	0.143
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 118	Outcome = Compliant	<0.001	0.857
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 475	Outcome = Non-compliant	<0.001	0.250
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 475	Outcome = Compliant	<0.001	0.750
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 661	Outcome = To be rechecked	<0.001	0.454
Supplier code = 7, Sample size = 15%, Product category = Bags, Article material = 661	Outcome = Compliant	<0.001	0.545

V. CONCLUSION

Quality management represents a relevant topic in the current industrial scenario and requires appropriate strategies to extract useful knowledge from data. In this sense, this paper presented an application of a data-driven approach to analyse historical data regarding the outcomes of quality controls. Such analytics approach allows to consider the sampling rules currently implemented and suggest their possible arrangement. In this way, the sample size can be adapted depending on the performance of the supplier, both in general and relating to a specific product category or article material. The Association Rule Mining has been selected to deploy this application because of its ability to identify relations between different attributes in a dataset.

From a theoretical point of view, ARM applications to the fashion industry can be found, but their implementations mainly refer to defect predictions and they have not yet been applied to improve the sampling process. From a managerial perspective, the identification of targeted sampling rules represents a competitive advantage for companies, especially for the ones that belonged to dynamic industries like fashion one, where the trade-off between outstanding quality level delivered to customers and short lead times represents a critical success factor. This is guaranteed by the streamlined update of the dataset carried out through the data-driven approach, as demonstrated by the real case study application. The iterative application of the proposed framework, made on an easy-to-update dataset, supports companies to quickly readapt sampling rules to the frequent changes that characterised dynamic markets (e.g., new articles made by already used materials assigned to current or new suppliers), overcoming the limitations to be only referred to cross-industry guidelines like the UNI ISO 2859-1:2007 standard. On the one hand, the proposed data-driven approach avoids the risk of basing sampling size definition on out-to-date information. On the other hand, only the necessary quality control will be carried out according to the performance trend of each supplier.

In the proposed case study, suppliers' performances have been analysed step-by-step: starting from their general performance in terms of compliance or non-compliance, the analysis has been extended for those having less promising results, by detailing the attributes included in the Association Rules. Specifically, product category and article materials have been included, in order to identify whether product characteristics had an impact on the quality outcome. Thanks to these analyses, recommendations on how to modify the sample size per supplier have been provided to the company. Specifically, it has been found that the sample size could not be arranged for all the lots, since in some of them the quality characteristics were considered specifically critical (e.g., valuable products). In other cases, an adjustment of the sample size regarding the specific article materials has been suggested due to the unusually high rate of defects for the supplier.

The results proposed in this paper represent the outcome of a preliminary implementation of the approach. As further development, other product features, such as the seasonality, could be investigated, in order to understand if carry-over and new seasonal products require different sampling rules. Looking at the analysed company, in fact, no references to seasonality have been included, even if new products could be expected to need stricter quality controls than carry-over ones. The proposed approach can also be implemented in other market segments, such as footwear, as well as other industries facing the same criticalities in terms of finding an easy way to extrapolate useful knowledge from huge amounts of data.

REFERENCES

[1] A. K. Choudhary, J. A. Harding, and M. K. Tiwari, "Data mining in manufacturing: A review based on the kind of knowledge," *J. Intell. Manuf.*, vol. 20, no. 5, pp. 501–521, Oct. 2009, doi: 10.1007/s10845-008-0145-x.

[2] A. Crespo Márquez, A. de la Fuente Carmona, and S. Antomarioni, "A Process to Implement an Artificial Neural Network and Association Rules Techniques to Improve Asset Performance and Energy Efficiency," *Energies*, vol. 12, no. 18, p. 3454, Sep. 2019, doi: 10.3390/en12183454.

[3] P. Yildirim, D. Birant, and T. Alpyildiz, "Data mining and machine learning in textile industry," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 8, no. 1, p. e1228, Jan. 2018, doi: 10.1002/WIDM.1228.

[4] UNI Ente Italiano di Normazione, "UNI ISO 2859-1:2007," 2007. [Online]. Available: https://store.uni.com/p/UNII285901-2007/uni-iso-2859-12007-11390/UNII285901-2007_EEN. [Accessed: 27-Jun-2022].

[5] A. F. Kouedeu, J. P. Kenné, P. Dejax, V. Songmene, and V. Polotski, "Production and maintenance planning for a failure-prone deteriorating manufacturing system: a hierarchical control approach," *Int. J. Adv. Manuf. Technol.*, vol. 76, no. 9–12, pp. 1607–1619, Feb. 2015, doi: 10.1007/S00170-014-6175-Y.

[6] H. Rivera-Gómez, A. Gharbi, J.-P. Kenné, O. Montaño-Arango, and J. Ramón Corona-Armenta, "Joint optimization of production and maintenance strategies considering a dynamic sampling strategy for a deteriorating system," 2020, doi: 10.1016/j.cie.2020.106273.

[7] Z. Hajej, N. Rezg, and A. Gharbi, "Joint production preventive maintenance and dynamic inspection for a degrading manufacturing system," *Int. J. Adv. Manuf. Technol.*, vol. 112, no. 1–2, pp. 221–239, Jan. 2021, doi: 10.1007/S00170-020-06325-3.

[8] R. W. Samohyl, "Acceptance sampling for attributes via hypothesis testing and the hypergeometric distribution," *J. Ind. Eng. Int.*, vol. 14, no. 2, pp. 395–414, Jun. 2018, doi: 10.1007/S40092-017-0231-9/FIGURES/10.

[9] B. Bindi, R. Bandinelli, V. Fani, and M. E. P. Pero, "Supply chain strategy in the luxury fashion industry: impacts on performance indicators," *Int. J. Product. Perform. Manag.*, vol. ahead-of-print, no. ahead-of-print, 2021, doi: 10.1108/IJPPM-02-2021-0079/FULL/PDF.

[10] S. Antomarioni, L. Lucantoni, F. E. Ciarapica, and M. Bevilacqua, "Data-driven decision support system for managing item allocation in an ASRS: A framework development and a case study," *Expert Syst. Appl.*, vol. 185, p. 115622, Dec. 2021, doi: 10.1016/J.ESWA.2021.115622.

[11] N. Ur-Rahman and J. A. Harding, "Textual data mining for industrial knowledge management and text classification: A business oriented approach," *Expert Syst. Appl.*, vol. 39, no. 5, pp. 4729–4739, Apr. 2012, doi: 10.1016/J.ESWA.2011.09.124.

[12] G. Köksal, I. Batmaz, and M. C. Testik, "A review of data mining applications for quality improvement in manufacturing industry," *Expert Systems with Applications*, vol. 38, no. 10. Pergamon, pp. 13448–13467, 15-Sep-2011, doi: 10.1016/j.eswa.2011.04.063.

[13] V. Kotu and B. Deshpande, *Data science: concepts and practice*, Second Edition. Morgan Kaufmann, 2018.

[14] C. Da Cunha, B. Agard, and A. Kusiak, "Data mining for improvement of product quality," in *International Journal of Production Research*, 2006, vol. 44, no. 18–19, pp. 4027–4041, doi: 10.1080/00207540600678904.

[15] J. Buddhakulsomsiri, Y. Siradeghyan, A. Zakarian, and X. Li, "Association rule-generation algorithm for mining automotive warranty data," *Int. J. Prod. Res.*, 2006, doi: 10.1080/00207540600564633.

[16] S. Antomarioni, M. Bevilacqua, D. Potena, and C. Diamantini, "Defining a data-driven maintenance policy: an application to an oil refinery plant," *Int. J. Qual. Reliab. Manag.*, vol. 36, no. 1, pp. 77–97, 2019, doi: 10.1108/IJQRM-01-2018-0012.

[17] C. K. H. Lee, G. T. S. Ho, K. L. Choy, and G. K. H. Pang, "A RFID-based recursive process mining system for quality assurance in the garment industry," *http://dx.doi.org/10.1080/00207543.2013.869632*, vol. 52, no. 14, pp. 4216–4238, 2014, doi: 10.1080/00207543.2013.869632.

[18] C. K. H. Lee, K. L. Choy, G. T. S. Ho, K. S. Chin, K. M. Y. Law, and Y. K. Tse, "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry," *Expert Syst. Appl.*, vol. 40, no. 7, pp. 2435–2446, Jun. 2013, doi: 10.1016/J.ESWA.2012.10.057.

[19] J. Han, H. Cheng, D. Xin, and X. Yan, "Frequent pattern mining: Current status and future directions," *Data Min. Knowl. Discov.*, 2007, doi: 10.1007/s10618-006-0059-1.