iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** III **Month of publication:** March 2022

DOI: https://doi.org/10.22214/ijraset.2022.40759

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

Order Prioritization Prediction System for Sample Rooms in the Garment Industry

Shirendra De Silva[1], Gayashini Shyanka Ratnayake[2]
[1, 2]*Informatics Institute of Technology, 57, Ramakrishna Road, Colombo-06, Sri Lanka*

Abstract: In the garment industry, one of the most prevalent industries in Sri Lanka, the process of sampling is key to gaining a competitive advantage in the market. The sample rooms in garment factories are considered the most important section in the readymade garments industry. Numerous processes occur in sample rooms, from perfecting patterns and quality checks on certain fabrics to confirming bulk production orders for prospective customers. Therefore, for these vital processes that occur in the sample room to function as efficiently as possible, they require the most accurate data. Research, including an initial pilot study done on a small to medium garment factory, suggests that approximately 35% of sample rooms in garment factories under utilise their capacity in accordance with demand. One reason being that most garment factories are based in developing countries, where the production focus is more labour intensive and less technology intensive. Not being able to accurately worker productivity metrics, coupled with a low merchandiser visibility on sample progression, would not allow the sample room to work on numerous pre-designs prior to the order. This hinders the chance for example, for designers to take on more simultaneous projects and approve bulk productions faster, resulting in potential losses for the organisation (Windmuller, 2020).
Keywords: SMV: - Known as Standard Minute Value, it is the value of the calculated accepted time to finish a particular garment job is known as the Standard Minute Value.

I. INTRODUCTION

Research conducted on local small to medium garment factories indicate that approximately 35% of small to medium garment factories sample rooms believe they under utilize their capacity in accordance with demand. Numerous factors could contribute to the issue.

A. Under use of Data on Operational Activity

In local and global apparel manufacturing sector, there are not many instances of companies effectively utilizing workforce data (Aksoy et al., 2014). With the catastrophe of the pandemic, where Sri Lankan and global supply chains were severely affected, the apparel industry incurred significant losses (Chakraborty, 2020). Global apparel sales dropped 25% during the pandemic. In Sri Lanka, there was also the human resource challenge, where employee work hour restructuring was required to optimise on peak hours (Welmilla, 2020). Having an effective productivity forecasting model with an order prioritisation would also help the Sample room efficiently reserve capacity.

B. Lack of Merchandiser Visibility

In the garments manufacturing process, the merchandiser plays a pro-active role, where she/he would have to follow all the activities from internal/external communication to preparing purchase orders. The merchandiser should understand the specifications and requirements of the buyer to produce samples (Cheng et al., 2021). Some small to medium garment manufacturing organizations face the issue of merchandisers not having real-time product-wise visibility on patterns and fabric approved samples. This is a significant issue as merchandisers are the individuals who dispatch the developed sample to the prospective buyer and complete the approval for bulk production, which is a variable cost that must be scaled effectively.

C. Quality Check Errors

Garments run through a multitude of quality checks before it is approved for bulk production. In factories that have not yet embraced certain aspects of technology, there is the issue of rejection grouping errors. (Refer Appendix D). This is where a faulty garment which did not meet the buyer specifications get classified into a group with a description for rejection for further analysis. These are when a finished sample does not meet the buyer specification, it is filed for rejection, and in some instances, it is not grouped properly. This leads to a higher chance of faulty decisions due to human error and is excessively time consuming (Islam et al., 2013).

D. Raw Material Sourcing Issues

With the pandemic disrupting supply chains, there was an evident shortage of raw materials in Sri Lanka and globally (Chakraborty, 2020). As a demand slump with the advent of the pandemic was evident, manufacturers had to manage costs, which included efficiently handling the raw materials that were currently in stock to avoid incurring even more running costs, such as weekly government mandated covid tests on garment company employees. This could mean reselling to other manufacturers or material suppliers. As most garment companies lock in 2–3-year manufacturing contracts with particular companies, effective raw material management is key.

E. Dependency on Traditional Communication

Garment factories that have not yet embraced aspects of digital transformation have occasional issues with communication (Refer Pilot study in Appendix D). Internal to external requirements passing from sample rooms in most small to medium garment factories would be done using excel sheets and emails. This has a high potential to lead to employee miscommunication on certain efficient decision makings on samples. This leads to time delays on pattern design approval and when confirming bulk production orders for prospective customers (Kuruppu, 2018).

F. State of Garment Industry

With the detriment caused by the covid-19 pandemic, the textile and apparel sector are hopeful of attaining much-needed development in 2021, with COVID-19 making 2020 a year of learning and upheaval (Tareque et al., 2020) In Sri Lanka, 2020 apparel exports dropped, in some months, by a maximum of 30%.

The textile industry profited from market volumes in the first ten months of 2020, so the sector may make 2021 a year of progress by focusing on optimizing sales of apparels in certain target markets.

For many countries, small and medium companies are critical. Small firms have new challenges in today's economy because of increased variance and competitiveness brought on by globalization, despite their contributions to providing jobs and economic growth that has a positive impact on the world (Nargiza, 2017). Small and medium-sized businesses contribute both financial and human resources that is otherwise scarce. In addition, the pandemic caused a major disruption to the supply chain, resulting in organizations needing to restructure their inventory and deal with issues such as raw material sourcing.

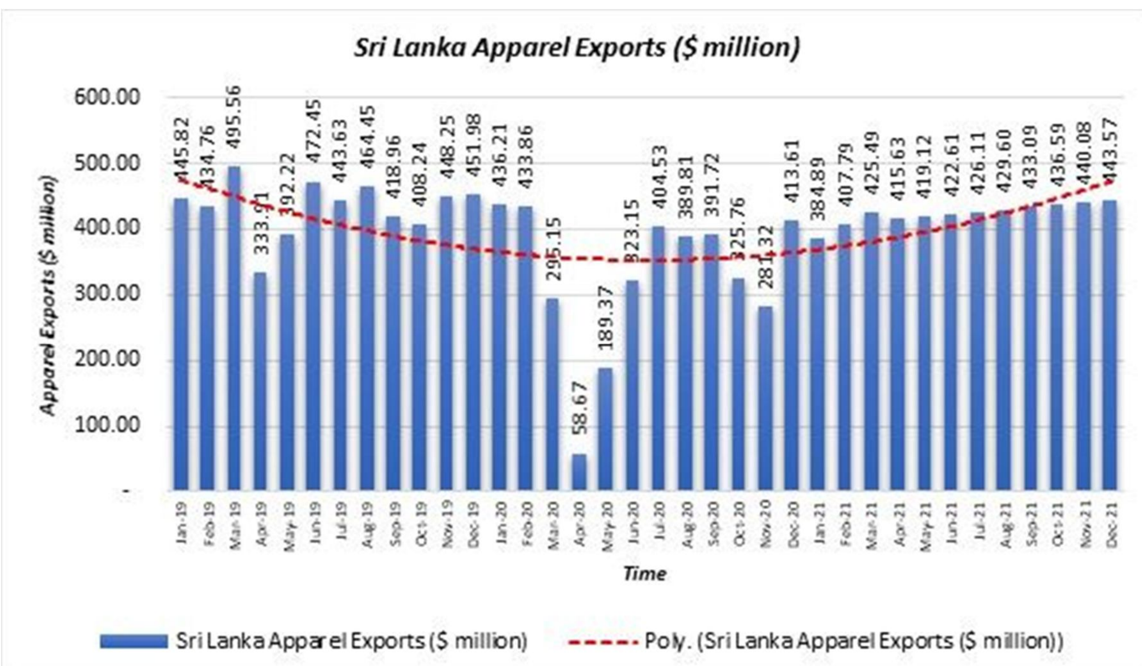


Fig 1.2 Sri Lankan Apparel export breakdown (2019-21)

According to (Duarte et al., 2021), a significant proportion of small-to-medium garment factories operate on what is informally called a fixed contract, which binds them to a manufacturing contract with a respective brand or retailer. This allows the organization to build familiarity between the brand and the variation of their product designs and requirements.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

II. RELATED WORK

To date locally, no capacity planning software used in Sample Rooms in the garment industry has an in-built tool for order prioritization and order queueing. But there are tools that allow manufacturers to manually compare the production loads against the available capacity to confirm orders. Therefore, the proposed solution was critically compared with those solutions.

A. IQMS 360

IQMS 360 is an enterprise resource planning (ERP) tool that is difficult to customize and requires a steep learning curve. IQMS contains functionalities for mapping the required business processes and manage inventory but its general functions that allow customization is challenging to adapt the sample room activities in the garment industry context. The only evident machine learning technique is the applications demand forecasting module which uses regression modelling to generate a demand forecast (Columbus, 2019). The drawback of this application is that its projected forecasts in some business instances do not match the true demand.

B. AX 365

AX is an ERP solution provided by the Microsoft corporation. The software solution is primarily used by organisations for operations management and finance tracking. Studies show that the systems general modules employ ML techniques for equipment monitoring and spam filtering. Other activities can be incorporated and customised into the solution but requires extensive internal/external training. The existing literature does not provide an insight on what machine learning techniques are used to achieve these processes (Zadeh et al., 2020).

C. Float

Float is a capacity management tool which is primarily used for resource scheduling and costing. This application Is used by small and large teams. Float has calendar integrations which can factor work holidays and forecast budgets. The Float tool is mainly used in Advertising and Marketing agencies, and Information Technology service companies. This tool can be customised for a Sample room use case, but it will have limitations. The disadvantage of adopting this tool is that it has heavy usage costs for the organisation. Along with the costs, it has no module which allows the customisation of wastage tracking into the forecasts, a forecasting metric which would be valuable for the merchandiser to make decisions on orders.

D. Fishbowl Inventory

Fishbowl Inventory is an inventory management software from the USA. According to Amoah (2017), the fishbowl inventory software contains modules in inventory control and material planning. In comparison to other software, fishbowl inventory is easier to have its modules customized for the required business case. After thoroughly reviewing the existing literature for the software, it is not clear what machine learning approaches the software uses. Overall, the software is useful for the basic capacity planning functions but does not have much support for extended functions in the operational aspect.

E. AIMS 360

AIMS is a fashion-based software mainly used for inventory management and style tracking. According to the available literature, this software employs machine learning techniques for their accounting modules processes. One of the specific functions on the accounting module of the AIMS 360 software is an invoice coding behaviour detection to automatically allocate transactions. Machine learning technology that recommends or completes accounting codes automatically reduces errors and saves time.

F. Limitations

The studies conducted on all reviewed applications which use machine learning techniques do not address certain aspects of operational efficiency which are applicable and adaptable to the sample room, most of which the proposed solution will be addressing (Guven, Uygun and Simsir, 2021). The aspect of expected efficiency for a given order, which can be calculated using the sewing operator assembly line average SMV (Standard Minute Value) for that type of order and the available workforce tasked with the order. The calculations can be generated using historical data of sewing operators for a similar type of order. This can be achieved using a Machine Learning approach. This is further emphasized by study conducted by Windmuller (2020), which provides an overview on potential adoptions of machine learning techniques into the garment industry capacity planning setting.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

This paper also highlights the advantages to the overall production speed when integrating some of the new approaches. Along with the expected efficiency, the insights on variance for an order can also be generated. Furthermore, each application reviewed does not factor in an approximate wastage checker for a bulk order, also which will be addressed in the proposed solution using a machine learning approach. This in turn, would directly improve the merchandisers visibility on production capabilities and allow them to decide on running more orders simultaneously (Liang, 2020).

III. PROPOSED SOLUTION

The proposed solution is planned to address these issues using machine learning and non-machine learning approaches.
The machine learning techniques used will be primarily built using these 3 libraries.

3.3 Libraries	Analysis	Risks
Caret	• Helps streamline methods for creating prediction models	• Complex library
DataExplorer	• Help for feature engineering and data reporting	• No autocomplete options
KernLab	• Useful for regression and clustering	• Errors difficult to debug

The machine learning approach taken will be of supervised learning, using previous orders styles and adjusting to the company updated SMV for a particular garment to generate the specified metrics of operational efficiency. The generic calculations for generating SMV are stated below.

Calculation of SMV in Garments

- SMV = Basic Time + Allowance
- Basic Time = Observe Time x Rating Factor
- Observe Time = Total Cycle Time/Number of Cycle
- Efficiency (%) = $\frac{\textit{Total Production} \times \textit{SMV}}{\textit{Total Man Power} \times \textit{Working Hour}} \times 100$
- Capacity (Piece) = $\frac{\textit{Total Time}}{\textit{Time Required for Making a Product}}$
- Target Production = $\frac{\textit{Working Hour} \times 60\ (\textit{Minute}) \times \textit{Number of Man Power}}{\textit{Standard Minute Value}\ (\textit{SMV})}$
- Costing SMV = Actual SMV + (Actual SMV x 5%)

The branch of supervised learning used in this proposed solution will be predictive analytics. Individuals, machinery, and other entities can be predicted using predictive analytics software applications that use characteristics that can be measured and analysed. Predictive analytics can be applied to a wide range of scenarios, which includes the above use case of Sample Rooms.
Choosing the suitable algorithm to implement will depend on the metrics that the proposed solution will be generating.
The level of accuracy for this solution will depend on two main factors when using supervised learning. The diversity of available labelled data and algorithm used. Surprisingly, high accuracy isn't always a good sign; it could indicate that the model is overfitting, or that it is overtuned to its training data set. When faced with real-world issues, such a data set may perform well in test settings but fail catastrophically when deployed into a real-world setting. The things that need to be considered when selecting a supervised learning algorithm: -

1) The first is the algorithm's bias and variance, as there is a narrow line between being flexible enough and being too flexible.
2) The complexity of the model or function that the system is attempting to learn is another factor. Before selecting an algorithm, it's important to consider the data's heterogeneity, correctness, redundancy, and linearity.
3) To generate Line efficiency (%) from the model, it will have to be trained with the inputs produced minutes and spent minutes. The equation for this output is

$$\text{Line eff (\%)} = \frac{\text{Produced minutes}}{\text{Spent Minutes}} * 100$$

4) In addition, to calculate capacity you take the Daily available minutes and the Product SMV
5) When taking the example of having to stitch 35,000 pieces where the
 Daily Shift = 10 hours
 Garment SMV = 26.5
 Manpower = 125 per line
 Number of lines = 4
 Line Eff varies from 15% to 50% as days progress

= (Daily Available minutes / Product SMV)
= (Daily Shift hours x 60 x Manpower x Line Eff% x Employee attendance %)/ Product SMV

In the first day of loading projected production capacity (when line Efficiency =15%)
= (10 x 60 x 125 x 15% x 95%)/26.50
= 403.30 pieces

In Day-2 production capacity (line efficiency 35%)
= (10 x 60 x 125 x 35% x 95%)/26.50
= 941.04 pieces

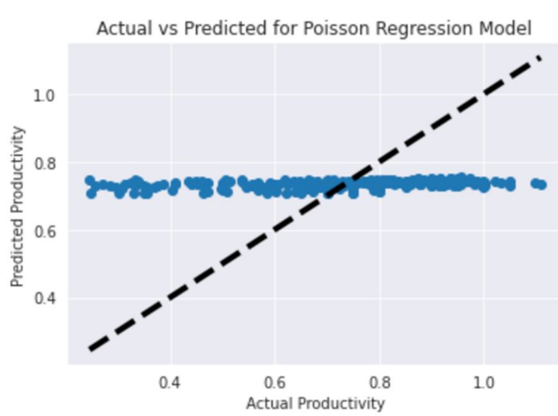
In Day-3 production capacity (line efficiency 45%)
= (10 x 60 x 125 x 45% x 95%)/26.50
= 1209.91 pieces

Day-4 onward projected line capacity will be (line efficiency 50%)
In Day-3 production capacity
= (10 x 60 x 125 x 50% x 95%)/26.50
= 1344.34 pieces

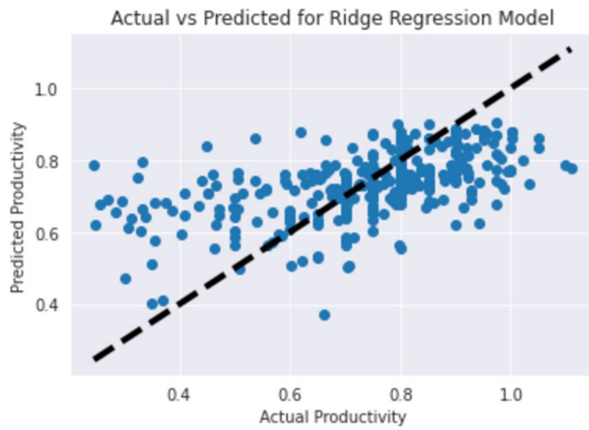
Day-wise total production capacity from 4 lines and cumulative production is shown in the following table. In the last day, lines don't need to work 10 hours to stitch the balance quantity.

The availability of historical data for creating a labelled dataset from the sample room data will vary from organizations depending on their respective company policies.

IV. SIMULATION RESULTS



International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com



Shown below are the respective RMSE (Root mean squared error), MAPE (Mean absolute percentage error), MSE and MAE for the respective approaches.

	models	mae	mse	rmse	mape	R2
0	Linear Regression	1.073137e-01	2.065111e-02	1.437049e-01	1.825055e+01	2.716789e-01
1	Lasso Regression	1.296462e-01	2.840179e-02	1.685283e-01	2.239547e+01	-1.671244e-03
2	Ridge Regression	1.031391e-01	1.989973e-02	1.410664e-01	1.783487e+01	2.981786e-01
3	Polynomial Degree 2	2.411213e+09	4.772471e+20	2.184599e+10	4.415495e+11	-1.683150e+22
4	Polynomial Degree 3	2.484805e-01	1.049795e-01	3.240053e-01	3.792991e+01	-2.702404e+00
5	Polynomial Degree 4	1.624107e-01	4.656320e-02	2.157851e-01	2.586959e+01	-6.421858e-01
6	Poisson Regression	1.267777e-01	2.743865e-02	1.656462e-01	2.196197e+01	3.229666e-02

Shown below are a list of tools to be used to implement the model.

Programming environments	Analysis
Visual Studio Code	• Highly interactive debugging • Assisted features such as bracket matching and snippets
R Studio	• Array of packages available for variety of data analytics projects

Hardware Requirement	Justification
Disk Space: Above 70GB	To run IDE, run model and run efficient information exchange
Processor: i5 or above	Minimum i5 processor required for running the application processes
RAM: above 8GB	8GB minimum required to run application without significant process lag

Database	**Analysis**
MongoDB	• High speed data retrieval
	• Easy method and function import

Security	**Analysis**
Azure storage service encryption	• Secure storage for data at rest

User Support	**Analysis**
Continuous system updates depending on user requirements	Keeping up to date with new practices
Customer support and feedback in-house	User query solved quickly
Training and on-boarding	Getting end users accustomed to new system

User interface
Consistency between module components
Purposeful page layout depending on functions
Strategic colour composition based on company theme etc.

V. CONCLUSION

The last few years have seen an exponential increase in the use of data driven decision making and forecasting in a wide span of industries. The garment industry in most instances, rely on labour intensive processes but could also benefit from the utilization of existing workforce data, which is the main aim of this paper.

A. Future Scope / Recommendation

What would be beneficial for the system in the future would be a system integration that includes a model to predict material costing. As this scope is extremely broad it will not be explored in the near future.

BIBLIOGRAPHY

[1] Aksoy, A., Öztürk, N. and Sucky, E. (2014), "Demand forecasting for apparel manufacturers by using neuro-fuzzy techniques", Journal of Modelling in Management, 9 (1), pp. 18-35.
[2] Bertola P., J. T., 2018. Fashion 4.0 Innovating fashion industry through digital transformation. Research Journal of Textile and Apparel, 22(4), pp. 33-56.
[3] CARDOSO, A., OLARU, S., GHITULEASA, P., DASCALU, M. and SOCOL, S., 2019. SKILL NEEDS AND GAPS IN QUALIFICATIONS FRAMEWORKS IN THE ROMANIAN CLOTHING INDUSTRY. TEXTEH Proceedings, 9, pp.16-55.
[4] Chakraborty, S., Chandra, M. & Biswas, 2020. Impact of COVID-19 on the textile, apparel and fashion manufacturing industry supply chain : Case Study on a ready-made garment manufacturing industry. Journal of Supply Chain Management, Logistics and Procurement, 3(2), pp. 181-199.
[5] Guven, I., Uygun, O. & Simsir, F., 2021. Machine Learning Algorithms with Intermittent Demand Forecasting: An Application in Retail Apparel with Plenty of Predictors. 31(2), pp. 99-110.
[6] Lüdecke, D., M. S. B.-S. I. P. a. D. M., 2020. Extracting, Computing and Exploring the Parameters of Statistical Models using R. Journal of Open Source Software, 4(5), pp. 1-5.
[7] Nargiza, M., 2017. National textile export capacity and effectiveness of the international market trends. Asian Journal of Marketing and Management Research, 6(1), pp. 1-13.
[8] Ratnajeewa, D. & Lokugamage, S., 2015. A Survey on Factors Affecting Supply Chain Management Effectiveness: A Case on Textile Sector in Sri Lanka. Colombo, Proceedings of 8th International Research Conference, KDU, Published November 2015.
[9] Saiful Islam, M., A. R. a. A. A., 2016. Ready-Made Garments Sector of Bangladesh: Its Contribution and Challenges towards development. J. Asian Dev. Stud, 5(2), pp. 50-61.
[10] Silva, C. & Chi, T., 2020. Automation Trends in Apparel Manufacturing. International Textile and Apparel Association Annual Conference Proceedings, 77(1), pp. 44-68.
[11] Tareque, A. & Islam, N., 2020. Leading the Digital Age: The Perspectives of the Readymade Garments Sector of Bangladesh. International Journal of Business Management, 03(12), pp. 01-13.
[12] Windmuller, S., 2020. Smart capacity planning: A machine learning approach, Innsbruck: s.n.
[13] Zied Jemai, Imen Safra, Jebali, A. and Asma Ghaffari (2018). Capacity planning in textile and apparel supply chains. [online] ResearchGate. Available from https://www.researchgate.net/publication/325214895_Capacity_planning_in_textile_and_apparel_supply_chains
[14] D. Bzdok, M. Krzywinski and N. Altman, “Machine Learning : Supervised Methods,” HHS Public Access, vol. 15, no. 1, pp. 5-11, 2018.
[15] Dutta Roy S. (2016) SAP BusinessObjects BI Platform. In: SAP Business Analytics. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4842-1383-4_5
[16] Kalra, S. and Sood, S.K. (2015). Secure authentication scheme for IoT and cloud servers. Pervasive Web Computing, 24, pp.210–223.
[17] S. M. Musa and C. M. Mujosi, "Data Visualization," International Journal of Engineering Research and Advanced Technology, vol. 2, no. 12, pp. 6-15, 2016.
[18] Choetkiertikul, M., Dam, H.K., Tran, T., Ghose, A. and Grundy, J. (2018). Predicting Delivery Capability in Iterative Software Development. IEEE Transactions on Software Engineering, 44(6), pp.551–573.
[19] Ramakrishnan, R., Sridharan, B., Douceur, J.R., Kasturi, P., Krishnamachari-Sampath, B., Krishnamoorthy, K., Li, P., Manu, M., Michaylov, S., Ramos, R., Sharman, N., Xu, Z., Barakat, Y., Douglas, C., Draves, R., Naidu, S.S., Shastry, S., Sikaria, A., Sun, S. and Venkatesan, R. (2017). Azure Data Lake Store. Proceedings of the 2017 ACM International Conference on Management of Data.
[20] M. A. Kamal and H. W. Raza, "Highlight the Features of AWS, GCP and Microsoft Azure in selecting CSP," International Journal of Recent technology and Engineering, vol. 8, no. 5, pp. 212-256, 2020.
[21] M. L. Waskom, “seaborn: Statistical data vizualisation,” The Journal of Open-Source Software, vol. 6, no. 2, pp. 3-11, 2021.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

SURVEY

A. Analysis and findings

1) Merchandiser requiring more visibility on processes

The relevant queries were included in the respective questionnaire in order to understand the local context regarding the contributing factors to the issue and to identify which areas can be improved regarding this particular aspect.

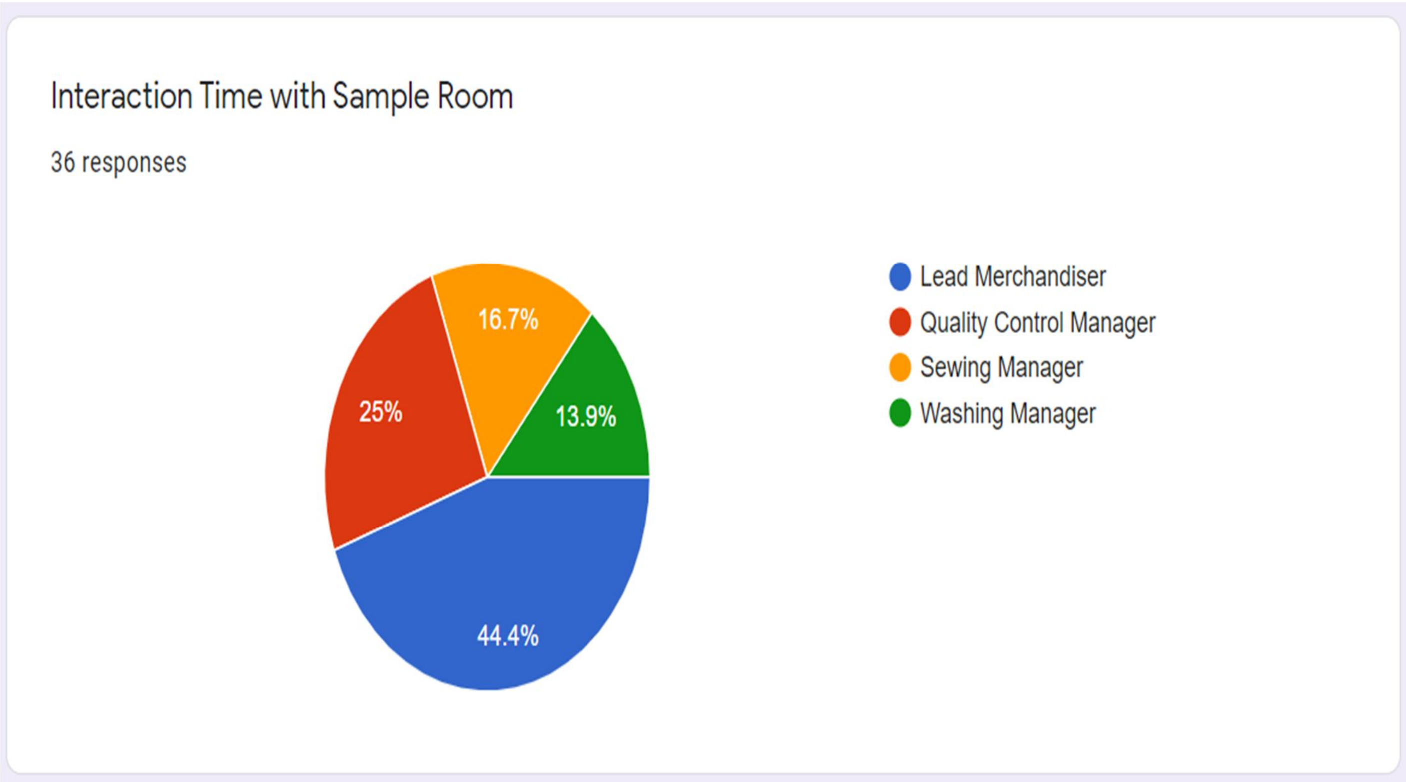


Figure 3-4: Interaction Time Breakdown

The results of the survey show 83.3% of respondents have external involvement and involvement in and around the sample room. Therefore, it supports the conclusions of Kader and Akhter (2014), that the sample room is the centralised point of the entire garment production process. Based on the gathered data during elicitation, Figure 3-4 indicates the overall interaction time with the sample room in a given period.

Findings suggest that key internal employees spend considerable amount of time in the sample room during the completion of an order. As seen in Figure 3-4, the lead Merchandiser in charge spends approximately 45% of their time in the sample room. Some of the main activities conducted by merchandisers are: -

- Pricing
- Fabric and Accessory consumption
- Product approval from buyer
- Pattern approval
- Unit costing

As the merchandiser makes the final decision with regards to whether an order is ready to be mass produced, it is key that they have full visibility of the ongoing processes. Therefore, it is evident that the Merchandiser requires full oversight on the processes during an order completion. As per Tharindu Gunasekara "for companies lacking large capacity for processing garments, it would be beneficial to gain a better understanding of the operational capabilities of the workforce". Figure 3-5 indicates the opinion of the response group on the above requirement.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

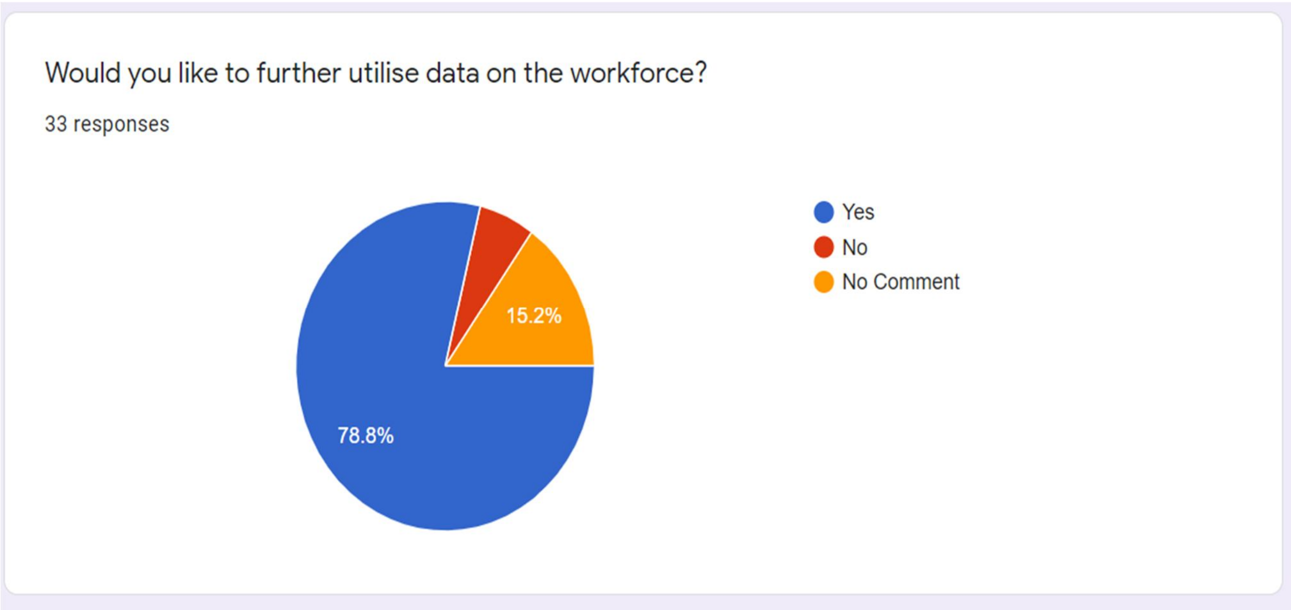


Figure 3-5: workforce data utilization

Responses illustrated in Figure 3-5 indicates that the majority of respondents would prefer further utilizing the data on operational efficiencies of the workforce. Figure 3-6 below shows what type of metrics they would prefer.

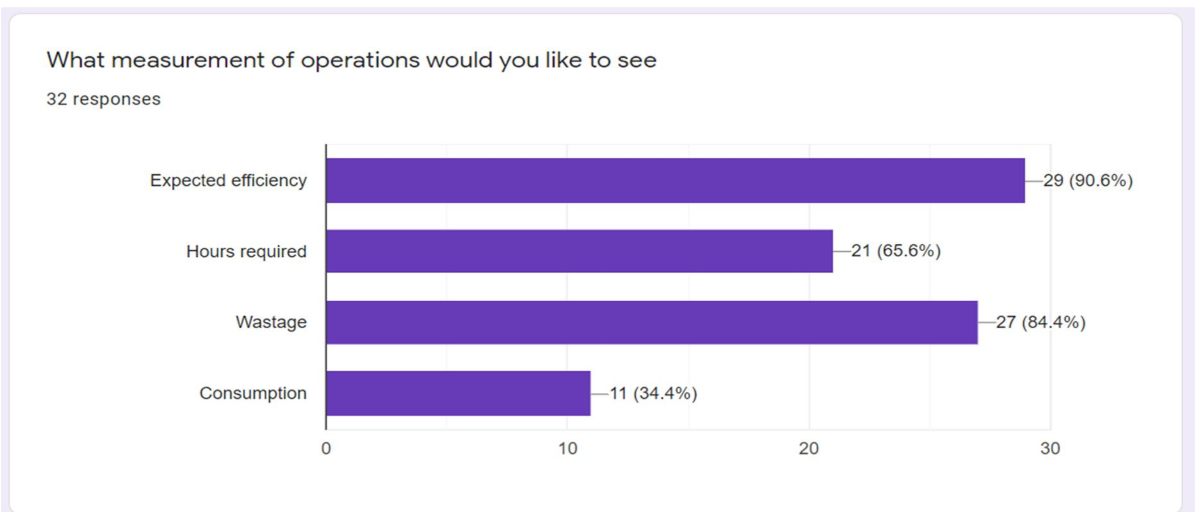


Figure 3-6: Operational metrics

The responses from Figure 3-6 indicate that the most required metrics estimate for an order are Expected efficiency and Wastage. From the 32 responses, 90.6% of the respondents believe that an estimate on expected efficiency would be effective. 84.4% believe an estimate on approximate wastage would be effective. 65.6% of the respondents believe an estimate for hours required for an order completion will be useful. 34.4% believe an estimate on average consumption would be useful. The findings prove that it will be valuable to gain these particular insights from the available data.

With the sampling process and its stages of pattern approval, washing, cutting, the majority of small organisations currently do not use a standalone application. Furthermore, in some instances, organisations tend to stick to traditional forms of communication such as excel sheets for order requisitions, which tends to be verified late and can lead to delays in lead time. Further issues tend to lead to numerous errors in when there is no standalone application used for this process. Responses from the questionnaire and preferences highlight the requirement.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

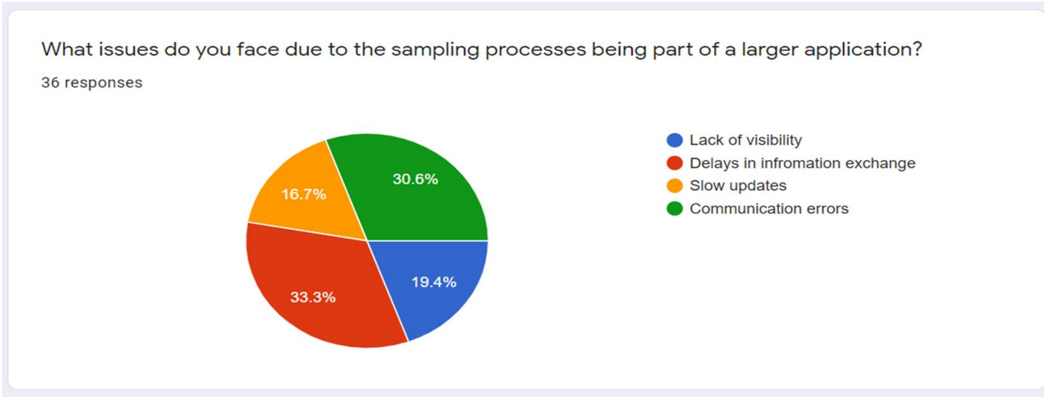


Figure 3-7: application preference

As some of the processes require further streamlining, reporting is also a key addition that would benefit the overall monitoring of the process. As per Kapil Ravindran "Reporting is a key feature that all teams involved in sampling would benefit from, whether it is a summary report for washing or cutting / embroidery. We currently use reporting in our system, but it would be beneficial for the reports to be updated faster ". Respondents of the questionnaire were asked what type of process reports would be helpful to have in a new standalone application.

Illustrated below are the responses from the questionnaire regarding reporting.

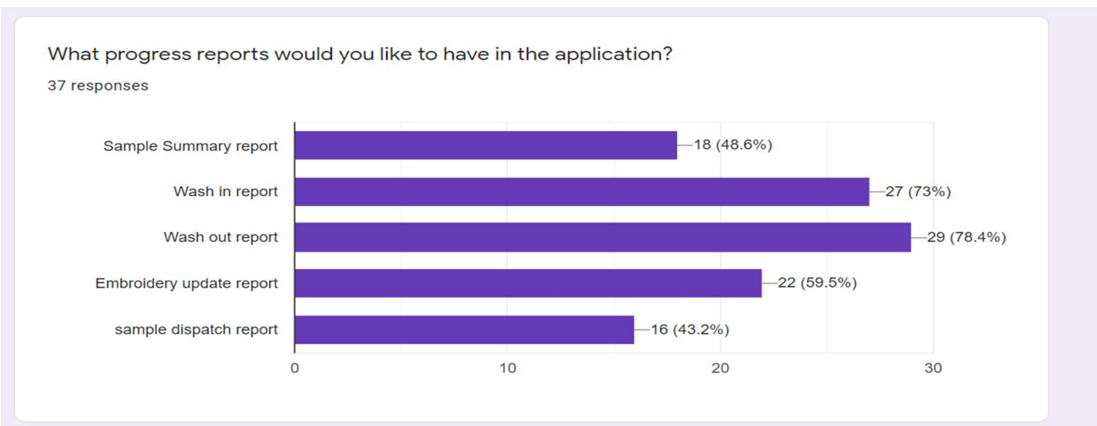


Figure 3.17 : Reporting

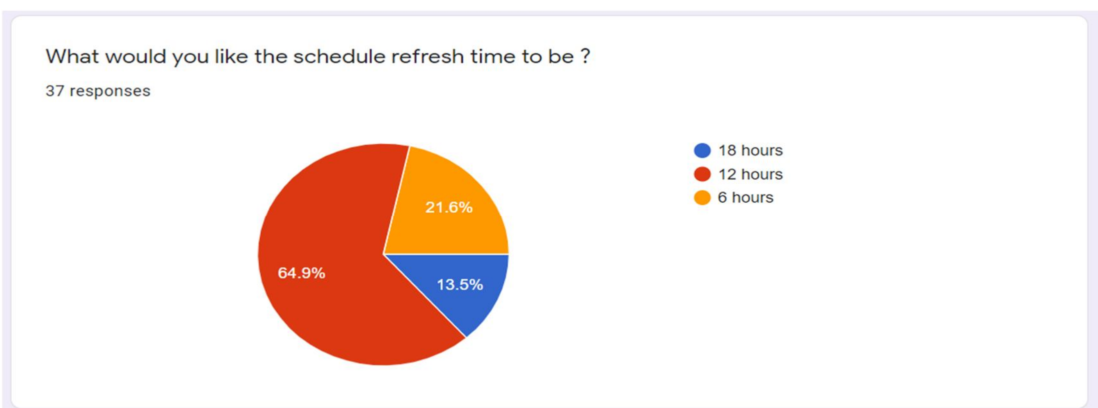


Figure 3.18 : Schedule refresh preference

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

According to the response analysis, the majority of respondents prefer their report schedule refresh time to be approximately 12 hours.

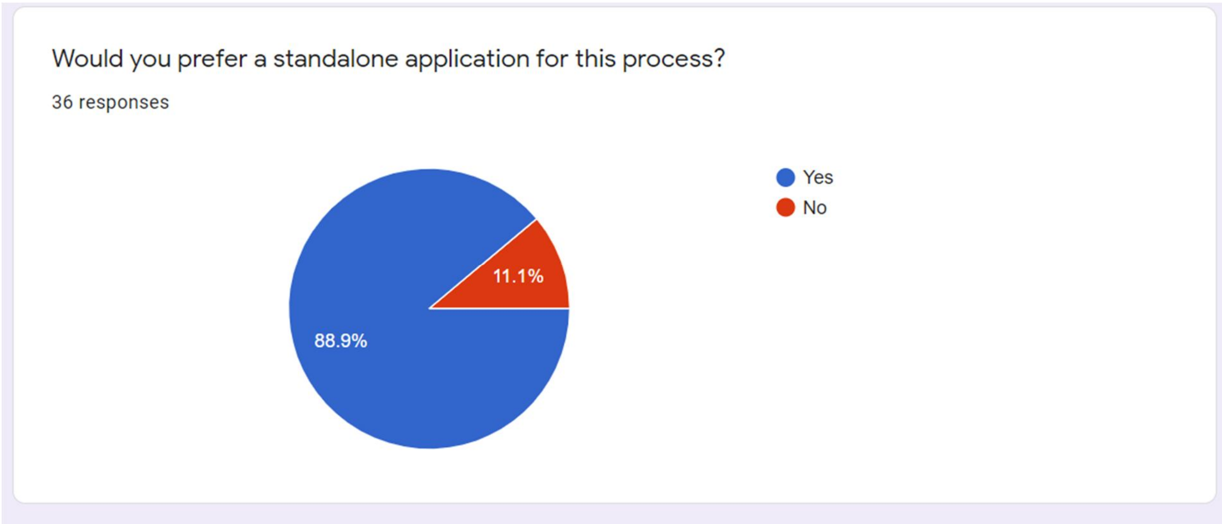


Figure 3-8 : Application preference

2) Covid-19 Pandemic affecting supply chain for raw materials

The COVID-19 epidemic wreaked havoc on global trade, economic, health, and education systems, as well as enterprises and society, like few other events in the last century. Some sectors were hit particularly hard with the disruptions to the supply chains, such as apparel companies. Figure 3-7 illustrates how 100% of the participating respondents of the questionnaire believe the covid-19 pandemic had a negative impact on their supply chain.

Figure 3-7

With the fluctuating demand and businesses closing their operations due to the pandemic, apparel companies in Sri Lanka and globally found it a struggle in some months during the year 2020-2021 to source some of the necessary raw materials to continue production of certain items. Figure 3-8 and Figure 3-9 elaborate which periods of the year respondents found it most difficult to source raw materials.

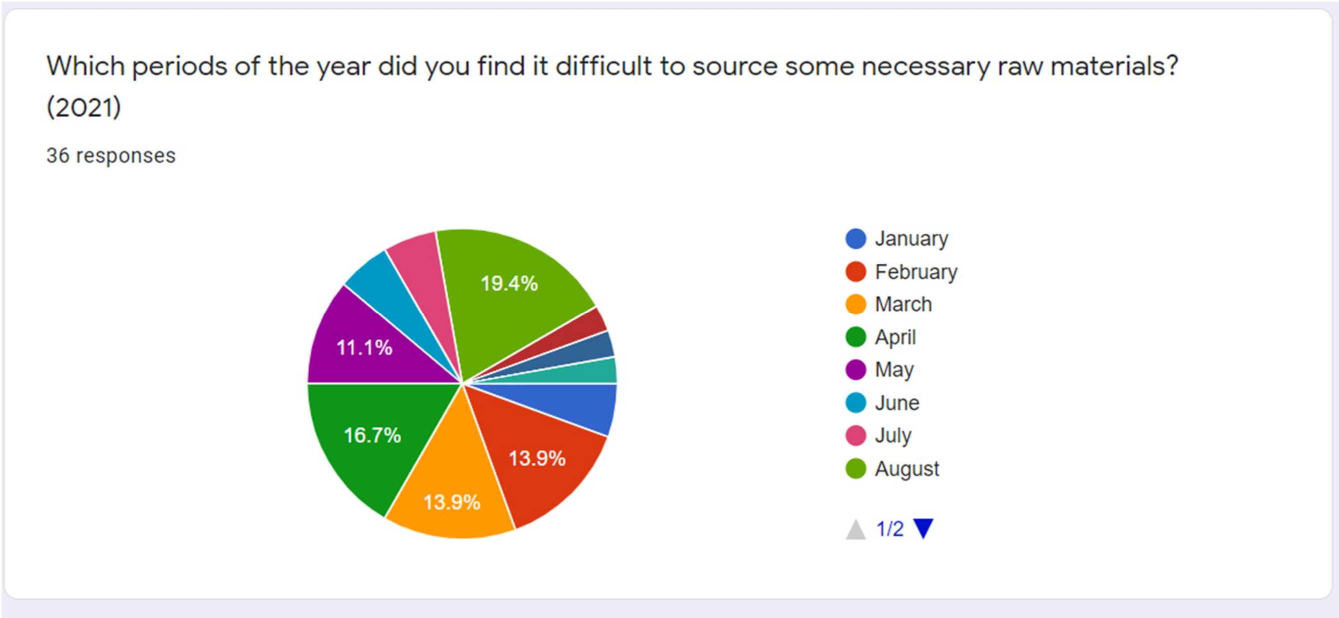


Figure 3-8

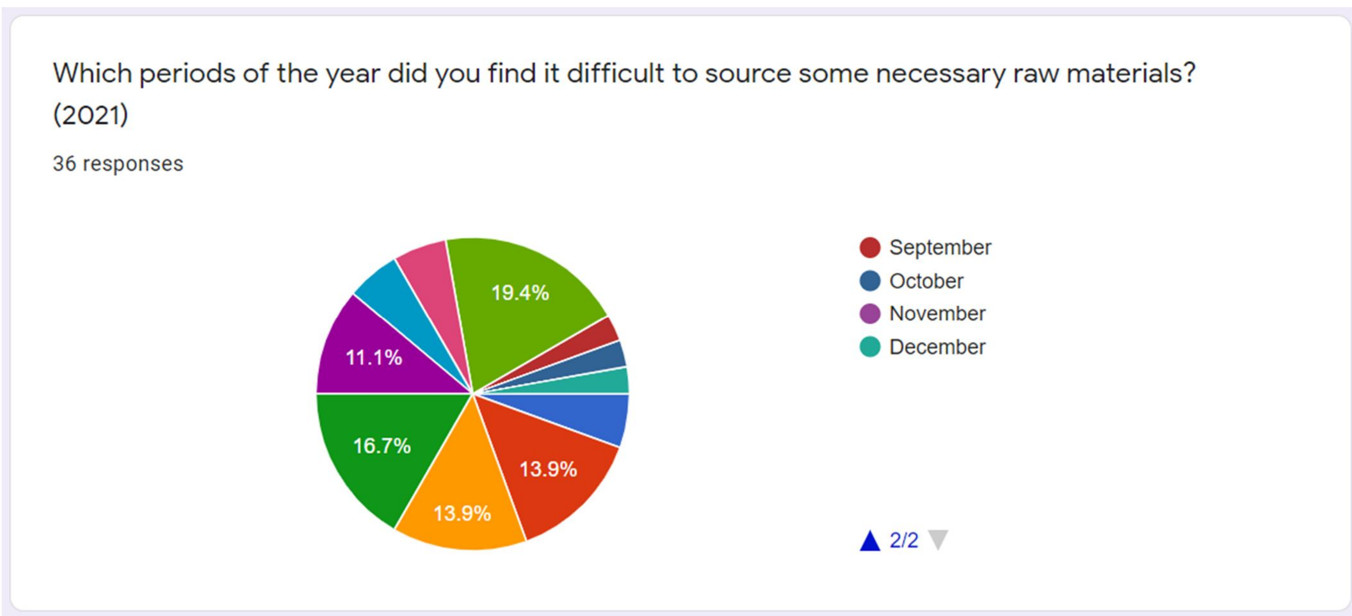


Figure 3-9

Figure 3-8 and Figure 3-9 prove that there were difficulties in sourcing raw materials during the year 2021. Analysis from the questionnaire responses show that 19.4% believe August was the most difficult month to source raw materials.

When discussed with Kapil Ravindran, he specified, “The industries with the most globalized operations and especially those that rely on Chinese inputs for manufacturing such as some garment companies in Sri Lanka were the most vulnerable to COVID-19's early supply chain disruption. The fashion sector confronts enormous dangers due to its non-essential nature. Indeed, because of COVID-19, consumers all around the world were no longer in need of new items. This industry is characterized by a worldwide supply chain that is highly interconnected.”

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

Figure 3-10 illustrates what type of raw material was difficult to source during the year 2021.

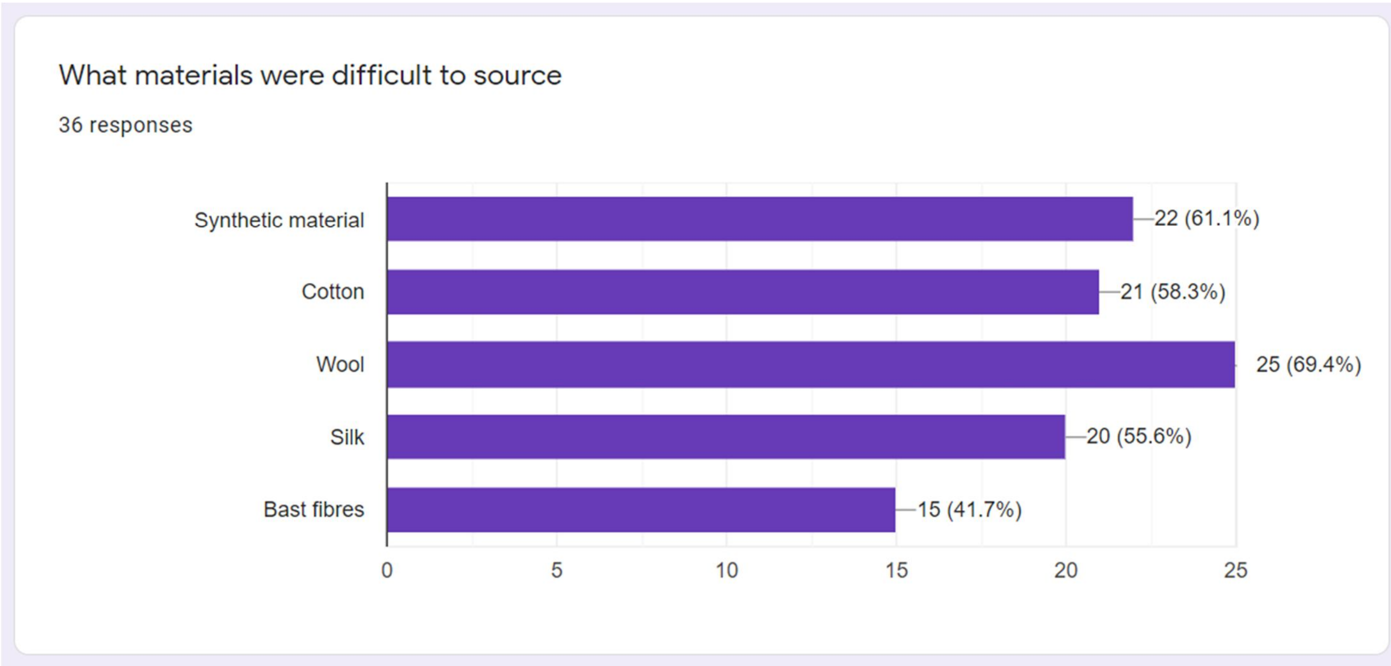


Figure 3-10

Responses illustrated in Figure 3-10 justifies what was discussed with K Ravindran during the interview regarding the negative impact faced by the Sri Lankan garment industry supply chain due to the Covid-19 pandemic. This further justifies the requirement for small garment organisations to effectively plan material sourcing for orders.

Respondents were asked to rate whether a more accurate system planning and overview for material costing and material planning along with wastage and consumption to better understand the overall production cost of the sample.

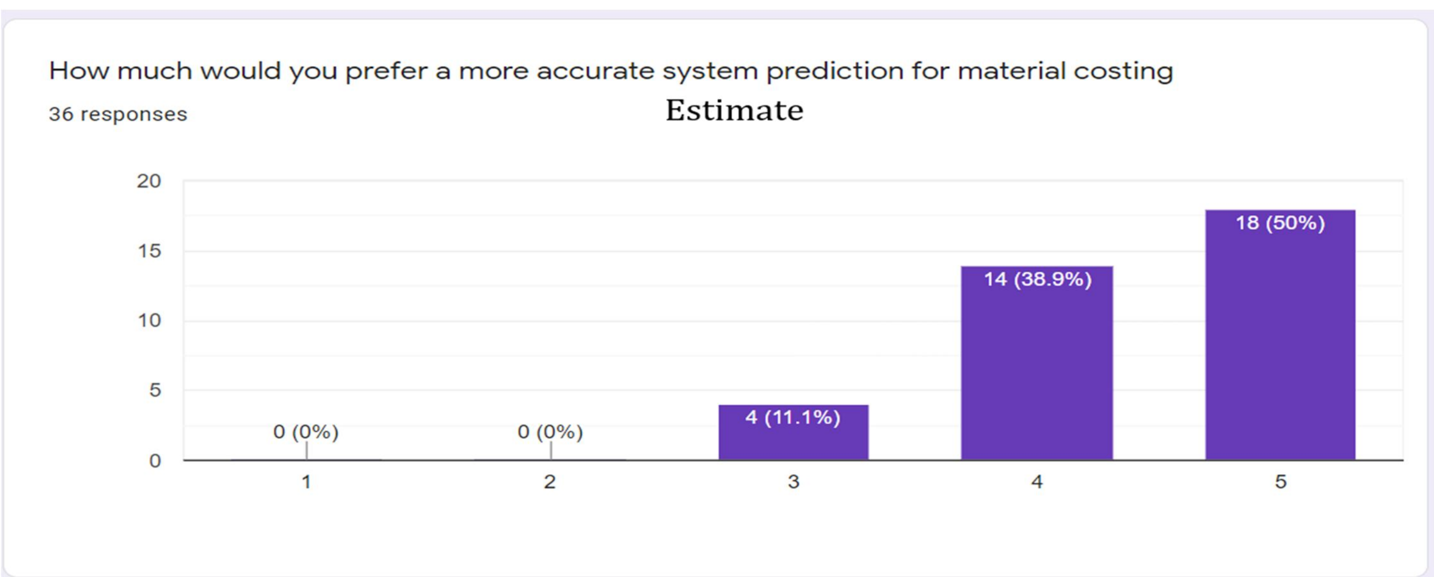


Figure 3-11

50% of respondents of the questionnaire rated it as highest rating of preferability, and 38.9% of respondents rated it as 4, the second highest. This justifies the requirement for this prediction for better overall material planning prior to approving production.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue III Mar 2022- Available at www.ijraset.com

3) Web Solution Preferences

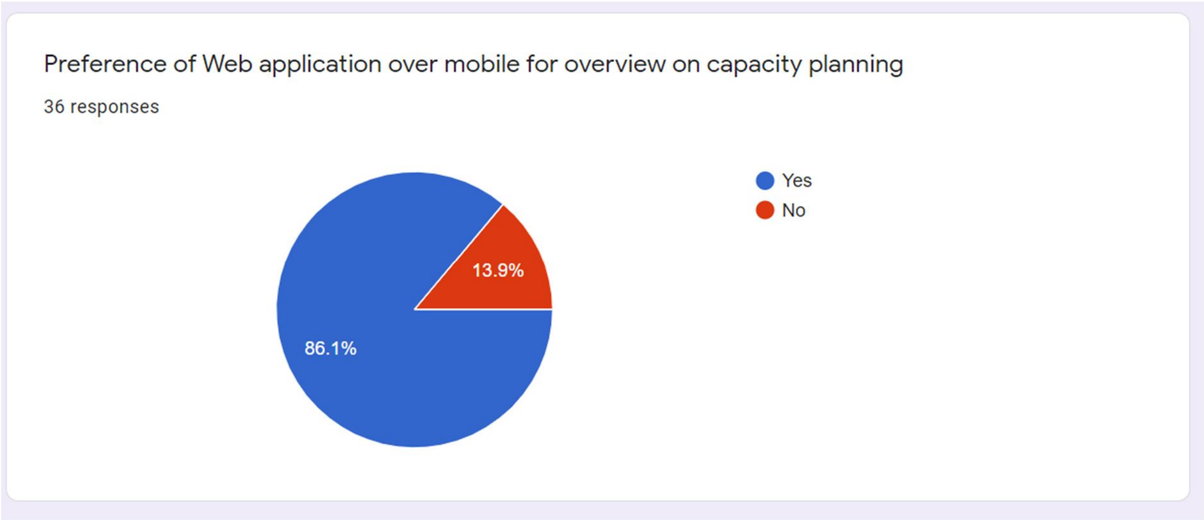


Figure 3-12

86.1% of the participants expressed their preference to use a web application over a mobile solution to effectively analyse workforce output, gain a transparent overview of the sample process prior to the approval of bulk production.

To further comprehend the willingness of the participants to use a web-based solution, comprehensive questions were added to the survey. The participants were asked to rate from 1 to 5 on the willingness to utilise the features of the proposed solution. The figures below show that participants rated 3-5 for all the proposed features to be implemented.

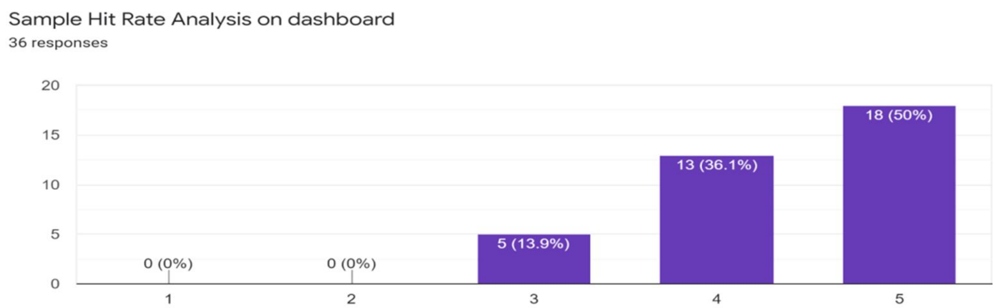


Figure 3-13 Sample hit Rate Analysis

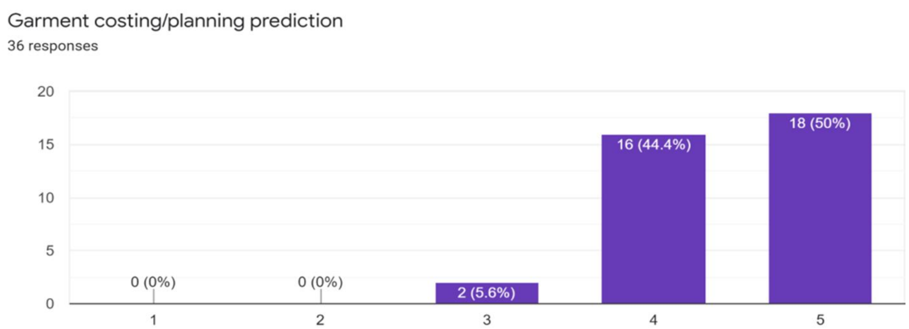


Figure 3-14 Garment costing/planning

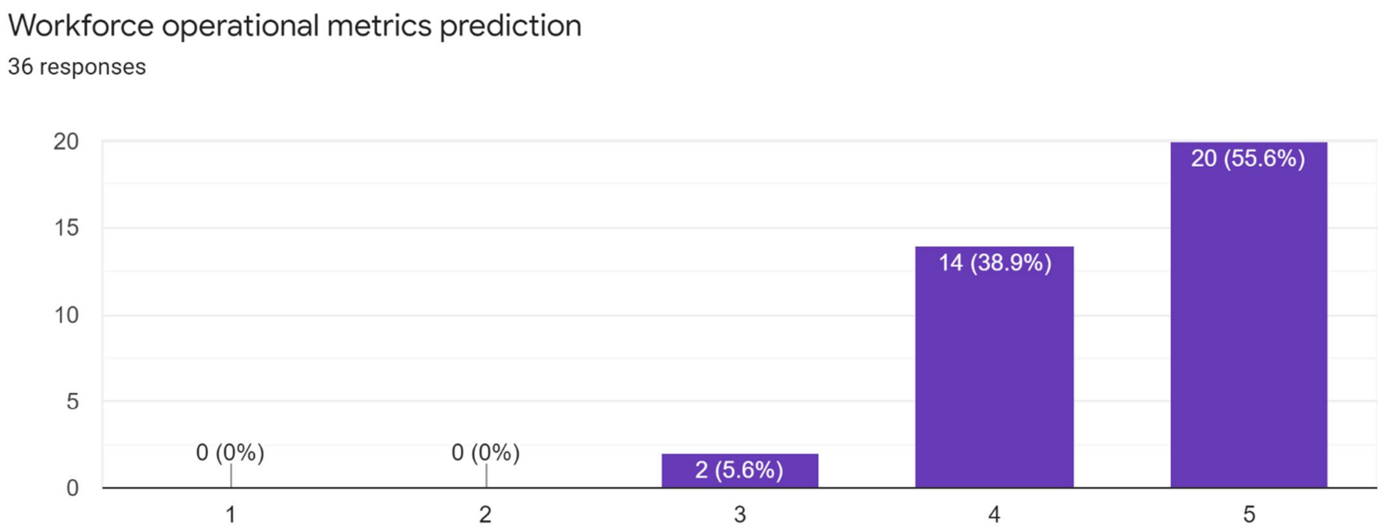
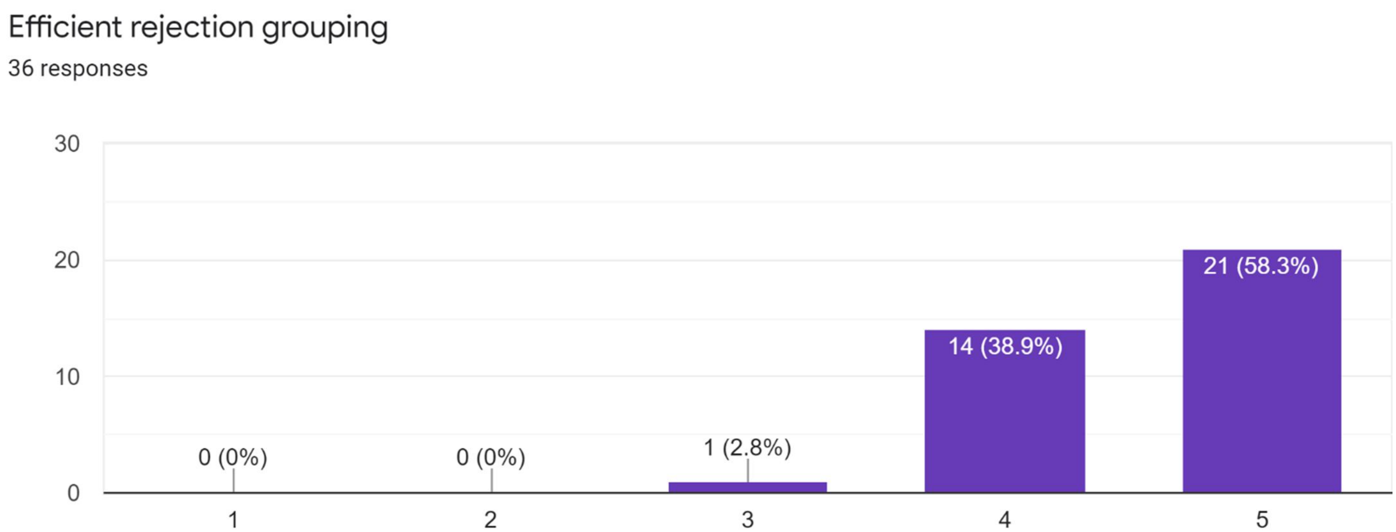
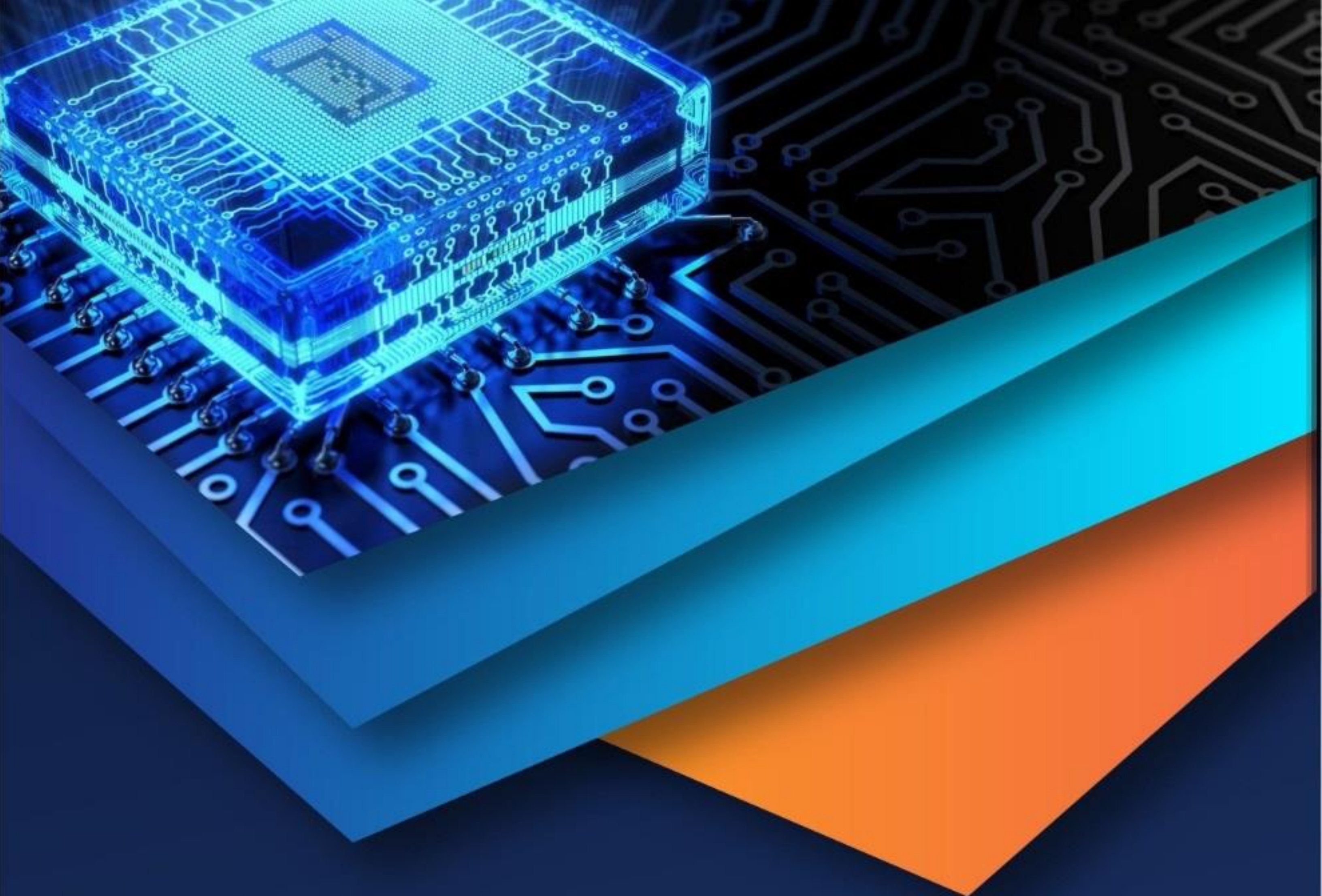


Figure 3-15 workforce operational metrics





10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY