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Modelling Learning in Technical Vocational Education Through Power Law: A Study of Textile Garment Machinery Operation

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Abstract

The development of practical competencies in technical and vocational education and training (TVET) has garnered significant interest in recent years, particularly in applying tools for measuring and understanding the learning process. This study aims to model and analyze the learning process of three high-performing students in operating straight stitch sewing machines using Wright's Learning Curve model. A non-experimental quantitative design with a descriptive scope was employed. Data were collected from three high-performing students during their learning process in operating straight stitch sewing machines. Wright's Learning Curve model (1936) was used for analysis, applying a logarithmic transformation to estimate parameters through linear regression. Model validation was performed using the coefficient of determination (R^2) and mean absolute percentage error (MAE%). Additionally, standard and total production times for 200 cycles were calculated using integral formulas. The model showed a good fit with determination coefficients between 0.69 and 0.74, and mean percentage errors between 12.97% and 19.74%. The standard times achieved for 200 cycles ranged from 23.23 to 62.13 seconds, with total production times between 79.13 and 211.88 minutes. These indicators provide measurable targets for planning vocational training in garment manufacturing, specifically concerning the operation and use of the sewing machine.

1. Introduction

Learning curves in industry focus on analyzing how learning improves over time by relating cycle time to the number of cycles through mathematical functions. This concept, initially introduced by T.P. Wright in 1936 in the context of aircraft manufacturing, has evolved into a foundational theory of industrial learning in general. Learning curves have been applied practically across various global industrial sectors. In this context, Niebel and Freivalds (2014) successfully applied learning curves to multiple cases in industrial engineering, using the Wright (1932) model, also known as the power learning curve. Similarly, the work of Rodríguez, Cespón, and Tovar (2022) addresses how learning curves influence supply chain logistics management. Their study focuses on measuring the impact of learning on lead time across different logistics management systems and presents an empirical analysis using log-linear models in three representative case studies based on the Supply Chain Operations model. To model the learning curve, the best-fitting model is selected from the following: Wright

Curve (1932), Plateau Curve (1949), Stanford B Curve (1964), De Jong Curve (1975), and S-Curve (1962), based on the criteria of Sum of Squared Errors (SSE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE).

Although the learning curve originated purely in an industrial context, its application has expanded to various professional activities, with a notable trend in the medical field. For example, Gao et al. (2024) applied learning curves to surgeons in an advanced program for rib fracture management. Two groups were compared: the first consisted of surgeons who developed the program and trained themselves, while the second group comprised surgeons mentored by those from the first group. Cumulative sum (CUSUM) analysis was used to evaluate operative time and errors, aiming to determine whether mentoring facilitated faster learning in the second group. The results showed that surgeons who received mentoring reached competency more quickly and had a more favorable learning curve compared to those who did not receive mentoring. Chen and Pei (2024) conducted a study that assessed the learning curve of the biportal endoscopic spinal surgery (BESS) technique using CUSUM analysis. A total of 144 patients from two centers were included, and it was found that surgeons with prior endoscopic experience achieved competency after 41 to 45 cases. Surgeons without prior endoscopic experience had more difficulty and eventually abandoned the technique. Previous endoscopic experience improved the learning curve for BESS.

The application of the learning curve in these studies can provide feedback on training processes and even determine the efficacy of various techniques in different fields, facilitating the identification of competency and the acquisition of new skills. An important factor in professional training is equipping students with the necessary skills that align with the real demands of the productive sector they belong to. In this respect, the application of learning curves offers the possibility of defining ideal work standards for future professionals. On the one hand, it allows defining learning and competency times based on real data, establishing clear and attainable expectations for skill acquisition. Additionally, it provides useful information for designing more efficient training programs by predicting how long it will take to reach different levels of competency, facilitating more effective planning. Another advantage is that it offers precise metrics to evaluate progress toward competency, allowing for adjustments in training methods to meet time standards. In this way, a quantifiable reference framework is established, determining the point at which professionals reach an optimal level of competency in performing specific tasks, within predefined and acceptable time parameters. This methodology not only provides a solid foundation for evaluating individual performance but also facilitates the implementation of continuous improvement strategies in the training environment.

The objective of this article is to evaluate and analyze the learning process of three students in the operation of a straight sewing machine, using the power law model to describe and quantify their learning curve. The equations modeling each student's production time are presented and compared, and indicators such as standard time, total production time, and learning percentage are calculated. The results and analysis have significant practical applications in the technical professional training within the garment manufacturing sector.

2. Methodology

The study involved three female students from the Advanced Technology in Textile Manufacturing program. This group demonstrated high proficiency in the use of basic straight sewing machinery. Their talent is reflected in their academic records in related subjects, and they have real-world experience operating straight sewing machines in professional environments, with 12, 5, and 3 years of experience, respectively. The study considered competencies related to cognition, technical skills, and abilities aligned with the program's graduate profile.

A test was administered to each participant, consisting of performing a series of work cycles to assemble a functional component onto a textile base. A cycle represents a complete repetition of a specific task or activity that the student is learning. In each cycle, the student attaches a zipper in a circular shape to a pre-prepared fabric using stitches and seams with a straight sewing machine. The test was classified as highly complex since the operator must maintain advanced skills and dexterity to execute stitches and seams along straight, curved, angular, and mixed lines. The precision operations required to complete this task are associated with the ability to recognize, visualize, select, grip, take, position, hold, and guide materials and tools.

The test was conducted continuously, without interruptions. During the test, an observer recorded the time taken at the end of each assembly cycle. This represents the time it takes for the student to complete one cycle of the task. A total of 20 cycles were documented, providing a comprehensive record of each participating student's performance.

For constructing the learning curves for each student, the Wright Curve model (1932) was used. This model describes how production time varies with the number of cycles, following the relationship:

$$y = a\, x^b \tag{1}$$

Where y is the production time in seconds, x is the number of cycles, a and b are adjusted parameters that characterize the relationship between y and x. To transform the Wright Curve model into a linear form, a logarithmic transformation was applied to the original equation, enabling the use of linear regression techniques to estimate the parameters a and b. The logarithmic transformation is expressed as:

$$log(y) = log(a) + b \cdot log(x) \tag{2}$$

Where $log(y)$ is the logarithm of the production time, $log(a)$ is the logarithm of the parameter a, and b is the exponent of the power law. The parameter a represents the time required to complete the first unit or cycle. It serves as a measure of the student's starting point. Meanwhile, the parameter b is the learning rate, indicating how quickly the student's performance improves with practice. A higher value of b implies faster learning. Several metrics were used to evaluate the model. The first is the coefficient of determination (R^2), which measures the proportion of variance in the data that is explained by the model. It is calculated according to the following formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

Where $\bar{y}$ is the mean of the observed values. This metric provides a measure of how well the model fits the data. The Mean Absolute Error (MAE) provides a measure of the average error in the model's predictions and is calculated using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2 \tag{4}$$

Where $|y_i - \hat{y}_i|$ represents the absolute difference between the observed values and the predicted values. The Mean Absolute Percentage Error (MAPE) is a metric used to evaluate the performance of a prediction model in relative terms. It is determined by the formula $MAE\% = \frac{MAE}{Valor\ real\ promedio} x100$ The last two metrics help quantify the average and percentage error, respectively, in the model's predictions. The standard time (ST) for one unit over n work cycles and the learning percentage are determined from Equation 1. Meanwhile, the total production time for n units is calculated using the following equation:

$$Total\,Time = TE(n) \tag{5}$$

For data processing, RStudio (version 2024.04.2+764) was used, an open-source integrated development environment (IDE) specialized for the R programming language (version 4.3.3). RStudio facilitates computational statistics and data analysis through a graphical interface that allows for writing, executing, and debugging R code. In the analysis, several functions were employed, including "lm" for performing linear regression and "log" for applying logarithmic transformations. The "lm" function allowed for fitting the linear model to the logarithmically transformed data, while "log" was used to linearize the relationship between the variables. The ggplot2 library was used to create a plot with the three modeled learning curves. The open-source nature of RStudio and ggplot2 promotes collaboration and transparency in the development and use of statistical tools, facilitating the implementation and validation of the analytical methods employed in the research.

3. Results

3.1 Model Definition

Table 1 presents the model parameters and key performance metrics for each student:

Table 1 *Model parameters and key performance metrics*

Parameter/Metrics	Student 1	Student 2	Student 3
A	252.787	246.114	92.4114
B	-0.264	-0.383	-0.2606
R^2	0.74	0.69	0.73
MAE	19.714	23.492	7.773
MAE%	12.97%	19.74%	14.59%

The analysis of the model parameters and metrics for the three students reveals key differences in their performance. Student 1 has the highest coefficient of determination R^2 (0.74), indicating a good fit of the model to their data. This suggests that the model is useful for predicting completion time for this student. However, Student 3 exhibits the lowest Mean Absolute Error (MAE) (7.77), implying greater accuracy in the predictions, although their MAE percentage (14.59%) is intermediate among the three, indicating that the relative error is not the lowest. Student 2 shows the fastest improvement rate with the most negative parameter b (-0.38), suggesting that they have the highest efficiency in reducing time with increasing cycles. Their absolute MAE (23.49) is the highest, and their MAE percentage (19.74%) is also the greatest, indicating that while they improve rapidly, their predictions are less accurate, and the relative error is more significant. In summary, while Student 1 provides the best model fit, Student 3 presents the highest accuracy in absolute predictions, and Student 2 demonstrates the best improvement rate, albeit with a higher relative error. The modelled learning curves are presented in the following figure:

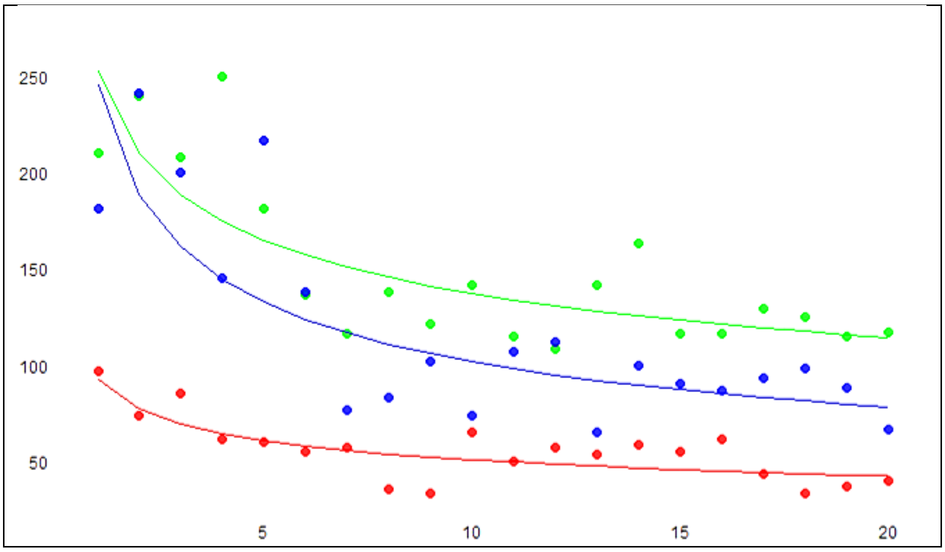

Fig. 1 *Time (y-axis) and number of work cycles (x-axis) along with the learning curves of each student. For Student 1 (green), the equation modelling the curve is* $\boldsymbol{y_1 = 252.79\, x^{-0.265}}$; for Student 2 (blue), it is $\boldsymbol{y_2 = 246.12\, x^{-0.38}}$; and for Student 3 (red), it is $\boldsymbol{y_3 = 92.31\, x^{-0.26}}$.

The graph displays learning curves for three students across multiple work cycles. Each curve represents how the time taken to complete a task (y-axis) changes as the number of work cycles (x-axis) increases. All three curves show a general downward trend, indicating that students become more efficient over time. The green curve (Student 1) starts highest and decreases gradually, maintaining the highest times throughout. The blue curve (Student 2) begins slightly lower than Student 1 but descends more steeply, eventually falling below the red curve. The red curve (Student 3) starts and remains the lowest, showing the fastest initial times and a gradual improvement. These patterns suggest different learning rates and starting proficiencies among the students, with all demonstrating improved performance as they gain more experience with the task.

3.2 Practical Applications

Below, we detail the process for calculating standard time indicators to complete a specified number of cycles, total production time, and learning percentage.

3.2.1 Standard Time to Complete N Cycles

The standard time to complete n cycles is determined using the Wright model (Equation 1). The standard time to complete 200 cycles for each student was calculated as follows $T_1 = 252.79\,(200)^{-0.265}$, $T_2 = 246.12\,(200)^{-0.38}$ y $T_3 = 92.31\,(200)^{-0.26}$. The standard time to complete 200 cycles is 62.13 seconds for Student 1, 32.28 seconds for Student 2, and 23.23 seconds for Student 3.

In the garment manufacturing industry, estimating the standard production time is a routine task. To define this metric, a time study is commonly conducted. In this traditional practice, the recorded time is taken from one or several operators with average performance. However, this method has a significant limitation: it generally does not account for the operators' learning curve. Calculating the standard time using the Wright model, as was done for the 200 cycles for each student, provides a more accurate estimate by incorporating the learning curve. This results in a more realistic assessment of the time required throughout the production process, especially for new products or operators.

3.2.2 Percentage of Learning

The percentage of learning is calculated as the percentage reduction in production time when doubling the number of units produced, using the following formula:

$$Percentage\ of\ learning\ = 1 - (2^{-b})\ x\ 100 \tag{6}$$

Where, b is the parameter of the model equation. The learning percentages for each student are as follows: for Student 1, $(1 - (2^{-0.265})\ x\ 100)\ \approx 54.770\%$; for Student 2, $(1 - (2^{-0.383})\ x\ 100)\ \approx 68.291\%$; and for Student 3, $(1 - (2^{-0.260})\ x\ 100)\ \approx 54.191\%$.

3.2.3 Estimation of Total Production Time

To calculate the total production time for 200 units, the integral method is used, represented by the following equation:

$$Total\ time{=}1nax{-}bdx \tag{7}$$

Where a and b are model-specific parameters and n is the number of cycles. Below is the calculation of the total production time for Student 1. Using the formula we have:

$$Total\ time{=}1200ax{-}bdx{=}ax1{-}b1{-}b1200 \tag{8}$$

With a=252.79 and b=0.265 and evaluating the integral, we get:

$$Total\ time = \left|\frac{252.79x^{1-0.265}}{1-0.265}\right|_1^{200} = \left|\frac{252.79x^{1-0.735}}{1-0.735}\right|_1^{200}. \tag{9}$$

By calculating at the upper and lower limits, we obtain:

$$Upper\ limit\ x = 200;\ \frac{252.79(200)^{0.735}}{0.735} \approx 13{,}056.83\ \text{seconds} \tag{10}$$

$$Lower\ limit\ x = 1;\ \frac{252.79(1)^{0.735}}{0.735} \approx 343.93\ \text{segundos} \tag{11}$$

Subtracting these values, we get 13056.83 seconds−343.93 seconds=12712.90 seconds ≈ 211.88 minutes. Applying the same procedure for Students 2 and 3, the estimated total production time for producing 200 units is 109.96 minutes and 79.13 minutes, respectively.

3.2.4 Summary of Indicators by Student

In the following table, a summary of the indicators for each student is presented, including the standard time for 200 units, the total production time for those units considering the MAE%, and the learning percentage.

Table 2 *Model parameters and key performance metrics*

Indicator	Student 1	Student 2	Student 3
Standard Time (200 cycles or units)	62.13 s (≈ 1.035 min)	32.28 s (≈ 0.538 min)	23.23 s (≈ 0.387 min)
Total Production Time for 200 Units, Considering MAE%	≈ 211.88 min ± 27.48 min	≈ 109.96 min ± 21.71 min	≈ 79.13 min ± 11.54 min
Learning Percentage	54.772%	68.291%	54.191%

As shown in the previous table, Student 3 exhibits the shortest standard time (23.23 s), followed by Student 2 (32.28 s) and Student 1 (62.13 s). This suggests that Student 3 is initially the fastest at completing a cycle, while Student 1 is the slowest. Regarding total production time, Student 1 requires the most time (211.88 ± 27.48 min), followed by Student 2 (109.96 ± 21.71 min) and Student 3 (79.13 ± 11.54 min). These times reflect each individual's overall ability throughout the execution of the 200 cycles, considering the learning curve. Student 3 maintains their initial advantage, completing the task in the shortest total time.

Student 1 has the highest absolute margin of error (±27.48 min), but the lowest relative margin. Student 2 shows considerable variability (±21.71 min), which may indicate less consistent performance. Student 3 has the lowest absolute margin of error (±11.54 min), suggesting a more stable performance. Student 2 stands out with the highest percentage of learning (68.291%), indicating a faster improvement with practice. Students 1 and 3 have similar learning percentages (54.772% and 54.191%, respectively), suggesting similar rates of improvement.

In general comparison, Student 3 demonstrates the best overall performance, with the lowest standard and total production times, and reasonable consistency. Student 2 shows the highest learning capability but with higher variability in their performance. Student 1, although starting with the lowest performance, shows consistent improvement and the lowest relative variability.

4. Discussion

The analysis of learning curves and performance metrics for three high-performing students in a straight sewing machine task provides a foundational understanding for refining and enhancing technical and professional training processes. The results reveal variations in learning rates and performance among the three students, who were already competent in operating the sewing machine. This demonstrates that even among skilled individuals, there is room for improvement and reduction in execution time. Student 3 exhibited the fastest initial performance and maintained the lowest total production time, while Student 2 showed the highest learning percentage, indicating rapid improvement over time.

These individual differences in skill refinement underscore the need for personalized learning approaches, especially for students entering programs with prior skills. This aligns with Magagula and Awodiji's (2024) work, which highlights the need for curriculum updates and enhanced instructional capacities at this level of training. The varying learning curves observed in our study, even among skilled students, support Yi et al.'s (2015) emphasis on improving internal and institutional processes in technical vocational training. Their research on dropout rates in technical vocational training underscores the importance of addressing institutional factors to prevent unfavorable situations for students, such as disengagement or dropout, even among initially high-performing individuals.

The practical implications of this study indicate significant applications in technical training and manufacturing industry contexts. Training planning can be optimized using data obtained from learning curves. For instance, the study demonstrated that it is possible to predict that a student with high initial performance can achieve a standard time of 23.23 seconds per cycle after 200 repetitions, while a student with a high learning rate but greater variability will require approximately 32.28 seconds per cycle. This data enables the establishment of estimated work targets for achieving better machinery mastery among students.

The analysis of learning curves also provides quantifiable metrics for progress evaluation. Results showed that the Mean Absolute Error (MAE) ranged between 7.773 and 23.492 seconds, with relative error percentages between 12.97% and 19.74%. This information allows for the establishment of acceptable performance variation ranges and realistic adjustment of improvement expectations. For example, for a student with a profile similar to Student 2 in the study, a 68.291% improvement in execution time can be expected when doubling the number of practice cycles.

In the industrial context, these findings have direct implications for production planning. The study demonstrated that the total production time for 200 units can vary significantly depending on the operator's profile, ranging from 79.13 minutes (±11.54 minutes) for highly efficient operators to 211.88 minutes (±27.48 minutes) for operators with lower initial speed. This variability, for instance, should be considered as a comparative element in the hiring of new operators and their time standards. Study results indicate that total production time can be improved through the implementation of personalized approaches. The 132.75-minute difference in total production time between the fastest and slowest operators in the study suggests considerable potential for improvement through personalized training. Continuous monitoring of these indicators, along with periodic adjustments based on observed performance, enables maximization of training process efficiency and improvement of productive outcomes in the industrial context.

It is particularly noteworthy that these results were obtained in a context of older students, suggesting that improvement and performance potential exists independently of operator age. This finding has important implications for hiring and training policies in manufacturing industry, where age has traditionally been given considerable weight as a limiting factor. The data demonstrates that, with appropriate methodology and a personalized approach, older operators can achieve and maintain competitive performance levels, thus challenging preexisting perceptions about the relationship between age and learning capacity in industrial environments. The significant differences in learning rates and performance metrics among already-skilled students suggest that curricula should include advanced modules designed to optimize existing skills and push the boundaries of performance. This aligns with Hasanefendic, Heitor, and Horta's (2016) observations on developing distinctive learning profiles in technical and vocational higher education. Their study on the role of technical and vocational higher education in Portugal emphasizes problem-based learning and short-term project-oriented research, which can be particularly beneficial for advancing the skills of already competent students. This supports Ogbuanya and Shodipe's (2021) argument regarding the importance of personalized workplace learning for enhancing teaching and learning quality. For students entering technical and vocational programs with existing skills, integrating more advanced, industry-relevant experiences into curricula could further enhance their learning curves and prepare them for high-level performance in real-world applications. This is particularly relevant in the context of the garment manufacturing industry, as discussed by Zakaria, Vouyouka, and Ruznan (2022). Their work highlights the importance of integrating technology for skill training, which is crucial for optimizing the performance of already skilled workers in the industry.

The varying performance levels observed among our already-skilled students highlight the need for technical and vocational programs to stay at the forefront of industry standards and technological advancements. This is particularly relevant in light of Poschauko et al.'s (2024) work on continuous technical and professional development in the automotive sector. Their study emphasizes the importance of implementing more precise tools, methods, and technologies, which is crucial for advancing the skills of already proficient workers. The detailed analysis of learning curves and performance metrics of the students in this study provides a quantitative basis for understanding skill improvement needs in technical tasks. This data-driven approach can strengthen the credibility of technical and vocational training institutions in providing advanced training, as suggested by Hasanefendic, Heitor, and Horta (2016). Moreover, the methodology used in this study, particularly the application of the Wright model and the calculation of various performance indicators for already-skilled individuals, offers a robust framework for assessing and predicting high-level student performance in technical tasks. This approach could be valuable for designing more effective advanced training programs and for industries in estimating productivity improvements and planning workforce development strategies for their employees.

While our study focused on high-performing students in a specific technical task, the implications extend to broader areas of technical and vocational training, particularly in advanced skill development. The approach used here could be adapted to assess and improve performance in other technical fields, as suggested by Raza et al. (2023). Their work on integrating disaster risk management in technical and vocational programs highlights the need for flexible and scalable training models, which could be particularly relevant for advancing skills in this critical area. The emphasis on developing a flexible and scalable capacity-building model aligns with our findings on the need for adaptable approaches to skill optimization for experienced professionals. Future research could explore how these learning curves and performance metrics vary across different types of technical tasks for students with varying levels of initial proficiency. Investigating how different advanced instructional methods impact these learning curves could provide valuable insights for optimizing technical vocational pedagogies for students entering programs with existing skills. Additionally, longitudinal studies tracking how initial high performance and subsequent skill optimization correlate with long-term career success could offer important insights for both training institutions and industries.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Msc. Rolando Ismael Yépez;* ***data collection****: Msc. Rolando Ismael Yépez, Msc. Diego Iván Flores;* ***analysis and interpretation of the results****: Msc. Rolando Ismael Yépez, Msc. Maricela Fernanda Ormaza;* ***draft manuscript preparation:*** *Msc. Rolando Ismael Yépez, Msc. Maricela Fernanda Ormaza. All authors reviewed the results and approved the final version of the manuscript..*

References

Chen, Z., & Pei, F. (2024). Learning curve of biportal endoscopic spinal surgery: A retrospective 2-center study. *World Neurosurgery, 187*, e543-e550. https://doi.org/10.1016/j.wneu.2024.04.123

Gao, A. Y., Whitrock, J. N., Goodman, M. D., Nathwani, J. N., & Janowak, C. F. (2024). The next generation: Surgeon learning curve in a mature operative rib management program. *Journal of Surgical Research, 301*, 461-467. https://doi.org/10.1016/j.jss.2024.06.041

Hasanefendic, S., Heitor, M., & Horta, H. (2016). Training students for new jobs: The role of technical and vocational higher education and implications for science policy in Portugal. *Technological Forecasting and Social Change, 113*(B), 328-340. https://doi.org/10.1016/j.techfore.2015.12.005

Magagula, M. M., & Awodiji, O. A. (2024). The implications of the fourth industrial revolution on technical and vocational education and training in South Africa. *Social Sciences & Humanities Open, 10*, 100896. https://doi.org/10.1016/j.ssaho.2024.100896

Ogbuanya, T. C., & Shodipe, T. O. (2021). Workplace learning for pre-service teachers' practice and quality teaching and learning in technical vocational education and training: Key to professional development. *Journal of Workplace Learning, 34*(4), 327-351. https://doi.org/10.1108/JWL-02-2021-0015

Poschauko, V. C., Kreuzer, E., Hirz, M., & Pacher, C. (2024). Engineering education goes lifelong learning: Modularized technical vocational education and training program for the automotive sector. *Procedia Computer Science, 232*, 1799-1808. https://doi.org/10.1016/j.procs.2024.02.002

Rodríguez Romero, Y., Cespón Castro, R., & Tovar Perilla, N. J. (2022). Estudio empírico sobre curvas de aprendizaje en sistemas de gestión logística. *Ingeniare. Revista chilena de ingeniería, 30*(4), 794-802. https://dx.doi.org/10.4067/S0718-33052022000400794

Raza, T., Raza, T. K. S., Pal, I., Peralta, J. F., Lim, H. A. M. P., Mayo, S. M., Liwag, C. R. E. U., Lopez, E. M., & Oinde, E. (2023). Mainstreaming disaster risk management technical and vocational education and training (DRM-TVET) program in higher education institutions: Flexible ladderized capacity building model amid COVID-19. En *Multi-Hazard Vulnerability and Resilience Building: Cross Cutting Issues* (pp. 249-279). https://doi.org/10.1016/B978-0-323-95682-6.00015-2

Raza, T., Raza, T. K. S., Pal, I., Peralta, J. F., Lim, H. A. M. P., Mayo, S. M., Liwag, C. R. E. U., Lopez, E. M., & Oinde, E. (2023). Mainstreaming disaster risk management technical and vocational education and training (DRM-TVET) program in higher education institutions: Flexible ladderized capacity building model amid COVID-19. En *Multi-Hazard Vulnerability and Resilience Building: Cross Cutting Issues* (pp. 249-279). https://doi.org/10.1016/B978-0-323-95682-6.00015-2

Zakaria, N., Vouyouka, A., & Ruznan, W. S. (2022). Sustainable apparel technical and vocational education and training (TVET): Integrating technology for skills training. En *Digital Manufacturing Technology for Sustainable Anthropometric Apparel* (pp. 3-21). The Textile Institute Book Series. https://doi.org/10.1016/B978-0-12-823969-8.00003-4

Yi, H., Zhang, L., Yao, Y., Wang, A., Ma, Y., Shi, Y., Chu, J., Loyalka, P., & Rozelle, S. (2015). Exploring the dropout rates and causes of dropout in upper-secondary technical and vocational education and training (TVET) schools in China. *International Journal of Educational Development, 42*, 115-123. https://doi.org/10.1016/j.ijedudev.2015.04.009

Zakaria, N., Vouyouka, A., & Ruznan, W. S. (2022). Sustainable apparel technical and vocational education and training (TVET): Integrating technology for skills training. En *Digital Manufacturing Technology for Sustainable Anthropometric Apparel* (pp. 3-21). The Textile Institute Book Series. https://doi.org/10.1016/B978-0-12-823969-8.00003-4

Yi, H., Zhang, L., Yao, Y., Wang, A., Ma, Y., Shi, Y., Chu, J., Loyalka, P., & Rozelle, S. (2015). Exploring the dropout rates and causes of dropout in upper-secondary technical and vocational education and training (TVET) schools in China. *International Journal of Educational Development, 42*, 115-123. https://doi.org/10.1016/j.ijedudev.2015.04.009