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Analysis of Learning Curves in a Social Enterprise: the Impact of a Disability on Learning and Production Output

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Henri Moerkens
June 2024

Scientific integrity

I declare that the research was conducted in accordance with the rules governing scientific and academic integrity. I have read, and acted in accordance with, the Code of Ethics of the Faculty.

Henri Moerkens
June 2024

Confidentiality of the master's dissertation

Table of contents

List of figures

List of tables

List of abbreviations

ADHD	Attention deficit hyperactivity disorder
ANOVA	Analysis of variances
ASD	Autism spectrum disorder
ERP	Enterprise resource planning
IQ	Intelligence quotient
ICD	International Classification of Diseases
LC	Learning curve
MSE	Mean Squared Error

Abstract

In this paper, the learning curves of disabled workers are analysed. Real data from a social enterprise was obtained. The most used learning curves in literature were fitted to 84 individual learning episodes. Knecht fit the data the best, followed by the hyperbolic model with 3 parameters and the Stanford-B model. Next, the impact of a disability on learning rate and productivity was analysed. The workers were classified into four categories: workers with cognitive disabilities, workers with psychological challenges, workers with a disability affecting the upper body and workers with a disability affecting the lower body. As the parameters of the Knecht's learning curve are difficult to interpret, the hyperbolic model was chosen for its explainability. The impact of a disability on output was statistically significant. With this specific task, workers with a disability affecting the lower body had the highest output, followed by workers with a disability to the upper body and workers with psychological challenges. Workers with a cognitive disability had the lowest output. The impact of a disability on the learning rate was not statistically significant.

1. Introduction

'Practice makes perfect', 'Übung macht den Meister', 'C'est en forgeant qu'on devient forgeron', 'Oefening baart kunst'… In almost every language, there is an expression that performance is correlated with experience. In the industry, this is also the case. If a worker is doing a job for the first time, they are unfamiliar with the job and will do it slowly. After a few times, they will learn the job and do it faster. The relationship between performance and experience follows a learning curve (LC).

The learning curve is an important tool in a production setting. The production cost per unit decreases when more units are being made. Learning curves can be applied to an organisation as a whole (where the organisation learns to work more efficiently) or a worker individually (where the worker gets more familiar with his task). Learning curves help companies better predict processing times, production output, and costs. Therefore, learning curves are an important tool in resource planning as well as process optimization. This thesis focuses on workers' learning curves.

WAAK is a social enterprise in Belgium. An organization that employs workers with a disability. Previously WAAK was a sheltered workshop, but because of changes in Belgian legislation, it was transitioned to a social enterprise in 2019. The company would like to know the impact of a certain disability on the learning rate and performance. At first, the company does not know what job to assign to which new worker. One of the products made by the company is wiring harnesses. Given the disability, the product and experience, the company wants to know what production output they can expect from a worker. Therefore, the company is interested in the impact of a disability on the learning rate and the output of the worker.

The second section of this master's thesis will focus on different mathematical formulations of the learning curves discussed in the literature. Furthermore, this section examines academic literature surrounding the impact of a disability on learning and output. Section 3 will analyse the Waak problem. In Section 4, the learning curves identified through literary analysis are fitted to the data and evaluated in terms of goodness of fit. In Section 5, the impact of a disability on learning and output is discussed, based on the best-fit learning curve found in Section 4. Section 6 presents the limitations and further research. The thesis concludes with Section 7, where the main findings are summarized.

2. Literature review

Section 2.1 discusses the different learning curves in literature. We will focus on the log-linear model and its modifications (2.1.1), on the hyperbolic models (2.1.2) and on the exponential models (2.1.3). Next, the performance of these different models in literature will be analysed (2.1.4). Section 2.2 focusses on learning with a disability and the performance of disabled workers.

This thesis only implements univariate models. Although theoretically useful, multivariate models are more complex to implement in practice. Furthermore, due to multicollinearity, they do not have a significant advantage over univariate models (Badiru, 1992).

2.1 Learning curves

Learning curves correlate the output or time to producing a unit with the number of units produced. As a company's production output increases, workers are expected to be more effective and efficient. The '80% learning curve' is widely used. The cost of producing a unit will decrease by around 20% every time the number of produced units is doubled (Anzanello et Fogliatto, 2011).

Anzanello and Fogliatto (2011) describe three families of learning curves. First, there is the log-linear model (and its modifications). Secondly, there are the hyperbolic models and thirdly the exponential models. Each family of models will be explained more precisely in the following subsections.

Workers' performance can be assessed in two ways. Firstly, one can look at how much time the worker needs to produce a product (hours/unit). If a worker learns, they will complete a task faster with repetition. The learning curve is a decreasing function. Secondly, one can also look at the number of units the workers make per hour (units/hour). In that case, as the worker learns, they will produce more units every hour. The learning curve is an increasing function. These two functions are each other's inverse. It is important to note that the log-linear model and its modifications focus on the time (or costs) to produce a unit. The hyperbolic and exponential models focus on the output per hour of a worker.

2.1.1 Log-linear model and modifications

The first paper on learning curves dates back to Theodore Paul Wright in 1936. He noticed that the labour costs of planes decreased with every additional plane build. Wright made use of a log-linear function to describe this performance (Wright, 1936). Therefore, this model is called the log-linear model or the Wright model.

$$y = y_1 * x^b \tag{1}$$

In equation (1), y represents the time or cost to produce unit x. y_1 is the time or cost to produce the first unit. b, a number between -1 and 0, is the learning rate and determines how fast the production time is reduced (Anzanello et Fogliatto, 2011; Glock et al., 2019).

This log-linear model can provide great insight into learning and how the production time will be reduced for further production runs. It can be applied in a wide variety of industries, for example in the chemical industry (Lieberman, 1984) and the truck manufacturing industry (Argote, 1999). Although it is a great model, it is not without limitations. Mathematically, if the production number is high enough, the production time will converge to 0. This is often not the case in practise (Eden et al. 1998). In addition to this, the model does not consider prior experience in which case the workers will learn much faster (Globerson et al., 1989). To solve those issues, adaptations were made to Wright's original model.

The Stanford-B model incorporates the prior experience of workers. The formulation is provided under (2). The additional parameter B refers to the number of units that the worker already has produced in the past. The other parameters remain the same as in the model of Wright.

$$y = y_1 * (x + B)^b \tag{2}$$

DeJong incorporated an additional parameter to describe the proportion of the task done by manual labour. It assumes that the throughput time of a machine is constant. This part cannot be shortened by experience. This can be translated into the learning curve, formulated under (3). M (0≤M≤1) is the incompressibility factor. If M=1, the entire process is done by machines and the cost of production remains constant over time. This formulation is often referred to as DeJong's model. Although the assumption that machines don't learn was certainly valid in the 20th century, modern developments in artificial intelligence can question this assumption. Oztemel and Gursev (2018) state that machines, especially robots, are capable of improving themselves autonomously.

$$y = y_1 * [M + (1 - M) * x^b] \tag{3}$$

The S-curve model combines the Stanford-B model and DeJong's model. The parameters have the same meaning as the previous models. It occurs when complex products are produced in combination with machines (Badiru, 1992; Nembhard et Uzumeri, 2000). Equation (4) describes the S-curve model.

$$y = y_1 * [M + (1 - M) * (x + B)^b] \tag{4}$$

The plateau model in equation (5) is the original log-linear model added with a constant C. This constant describes the steady state of the performance of the workers. When the worker fully finished learning his task, they will produce output C.

$$y = C + y_1 * x^b \tag{5}$$

Jaber and Guiffrida make also a modification of the original log-linear model to correct for the plateau effect. Equation (6) represents this model. The log-linear model does not assume rework. However, in practice, this is not the case (Jaber et Guiffrida, 2004; Jaber et Guiffrida, 2008).

$$y = \frac{y_1}{1 - b} * x^{1-b} \tag{6}$$

Levy modified the log-linear model by adding β, which is a task-defined production coefficient. k is the workers' performance in a steady state. The other parameters have the same meaning as before. The formula for the Levy's learning curve can be found in equation (7) (Levy, 1965).

$$y = \left[\frac{1}{\beta} - \left(\frac{1}{\beta} - \frac{x^b}{y_1}\right) k^{-kx}\right]^{-1} \tag{7}$$

Pegels proposed an alternative functional form, also based on phenomena in empirical data. In equation (8) A, a and b are empirically based parameters (Teng et al., 1983; Nembhard et Uzumeri, 2000).

$$y = A * a^{x-1} + b \tag{8}$$

One disadvantage of the Levy's and Pegels's learning curves is that their parameters are harder to interpret (Nembhard et Uzumeri, 2000).

2.1.2 Hyperbolic models

Mazur and Hastie (1978) introduced a new model where they looked at the amount of correctly produced units to the total amount of produced units. The formula can be found in equation (9). If a worker is still learning, some products that they produce contain an error. When the worker is learning, the share of badly produced units decreases. Mazur and Hastie (1978) use this property to make a learning curve. x represents the number of units produced of good quality. r is the number of units produced of poor quality. k is a constant to fit the learning curve. Therefore, y is the proportion of correctly produced units multiplied by constant k. This model is often called the two-parameter hyperbolic curve.

$$y = k * \left[\frac{x}{x + r}\right] \tag{9}$$

For learning purposes, these parameters can also be interpreted differently. As with the exponential models, y can represent the amount of units produced after x hours or units of training. r can be used as the learning rate (Nembhard et Uzumeri, 2000). k is a constant and is the maximal performance of a worker. It is the asymptote to which the curve converges. A low value of r would imply that the worker is a fast learner and the curve quickly converges to the asymptote. A big value of r means that the worker is a slow learner. If the worker is forgetting, r becomes negative. This implies a decline in performance or output over time.

An additional parameter p can be added to equation (9) to correct for the previous experience of the worker. This is the three-parameter hyperbolic curve, which can be found in equation (10).

$$y = k * \left[\frac{x + p}{x + p + r}\right] \tag{10}$$

The meaning of k and r is the same as the two-parameter hyperbolic curve. A bigger value of p would imply that the worker has more experience. p should always be positive.

2.1.3 Exponential models

The three-parameter exponential model is shown in equation (11). The parameters have the same meaning compared to the hyperbolic models. Mazur and Hastie (1978) compared the exponential and the hyperbolic model. They noticed that p and r have similar values in both models, however k is often underestimated by the exponential model. The hyperbolic model provided a better fit based on the R^2.

$$y = k * \left[1 - e^{-\frac{x+p}{r}}\right] \tag{11}$$

As with the hyperbolic model, there is also a two parameter exponential model. This model does not assume previous experience. p is set to zero, resulting in equation (12). This model gives a poorer fit compared to the three-parameter model (Mazur et Hastie, 1978; Nembhard et Uzumeri, 2000)

$$y = k * \left[1 - e^{-\frac{x}{r}}\right] \tag{12}$$

Knecht (1974) tried to create a better performing model by combining the log-linear model with the exponential model. He focused on long duration production runs, as the standard log-linear model converges to zero when lots of products are produced. The result of which can be assessed in equation (13). The definition of the parameters is the same as in the log-linear model. y refers to the time needed to produce item x. y_1 is the time to produce the first unit. c is an additional constant in this model.

$$y = y_1 * x^b * e^{c * x} \tag{13}$$

As with the Levy's and Pegels's learning curves, the Knecht's learning curve is more complicated to interpret compared to the other models.

2.1.4 Performance of the different learning models

As there are many different types of learning models, multiple studies have already compared the different models with empirical data. Nembhard and Uzumeri (2000) did a study on 13 learning models. They found that the three-parameter hyperbolic model is the best in terms of efficiency and stability. In their analysis, Nembhard and Uzumeri made use of data from a United States manufacturing organization where workers had to learn a new skill. This skill involved sewing which requires a high level of hand-eye coordination and manual dexterity. Anzanello and Fogliatto (2007) found that the three-parameter hyperbolic model is more robust compared to the three-parameter exponential model. Anzanello and Fogliatto used data from a shoe company. Here again, workers had to learn manual skills like sewing. However, to the best of our knowledge, there has not been a comparison for learning curves applied to workers with a disability. This paper will fill this gap by conducting a comprehensive analysis of learning curves among workers with disabilities performing a manual task.

2.2 Learning and working with a disability

Attention deficit hyperactivity disorder (ADHD) is a neurodevelopmental disorder defined by a consistent pattern of inattention and/or hyperactivity/impulsivity which disrupts one's functioning or developmental trajectory (N. A. P. Association, 2022). One of the first studies was done by Still in 1902 on young boys. Later, it was found that girls and adults also have similar problems and symptoms. It is found that around 5% of the population has ADHD (Smith, 2017). People with ADHD are more likely to have learning disabilities (N. A. P. Association, 2022). In the past years, the research focussed on young men and women in their adolescence. In tasks such as reading, mathematics or writing, 20% to 30% of the students with ADHD have a learning disability. Although not every student with ADHD has a learning disability, the correlation remains high (DuPaul et Volpe, 2009).

Autism spectrum disorder (ASD) or autism is another neurodevelopmental disorder. People with ASD have difficulties with social interaction and nonverbal communication, in combination with excessively repetitive behaviours, restricted interests and insistence on sameness (Aarons et Gittens, 1999; N. A. P. Association, 2022). The International Classification of Diseases (ICD-11), does not differentiate autism with or without intellectual disability (World Health Organisation, 2019/2021). However, ASD often co-occurs with an intellectual developmental disorder (N. A. P. Association, 2022).

To the best of our knowledge, the only study found to have applied learning curves on (mentally) disabled workers was published by Pooley and Bump in 1993. They investigated the learning curve of workers with intelligence quotients (IQs) between 60 and 80. They made use of the standard log-linear learning curve. An image of their findings is displayed in figure 1. The learning rate of mentally disabled workers was 85%, which is in the range of learning rates for non-disabled workers. The disabled workers had an initial time that was much higher compared to their non-disabled colleagues and for this particular task, their learning rate was higher. Non-disabled workers had a higher turnover rate and left the company after on average 21 000 units produced. Another non-disabled worker without experience has to replace him. This explains the increase in task time in figure 1. The disabled worker has a much lower turnover rate. Therefore, they will learn for a

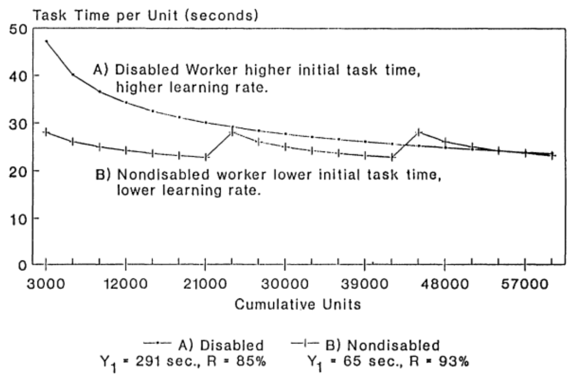

Figure 1: Figure from Pooley and Bump (1993).

longer time. Over time, the performance of the disabled worker is similar compared to the non-disabled worker. From a financial perspective, hiring workers with a disability is advantageous. Their performance over an extended period of time is similar to that of workers without a disability and the employer receives a job credit for employing disabled workers. Therefore, disabled workers are more cost-effective than non-disabled workers.

Although there has been extensive research on mental disabilities and their respective learning disorders, there has been little research on learning with a physical disability. Guimaraes and al. (2016) assessed the impact of a physical disability on productivity and the absence of workers. They performed their study on construction workers in Brazil. There were disabled as well as non-disabled workers. In the group of disabled workers, there were seven servants and one bricklayer. The majority of the disabled workers did not find that their disability hindered their performance. Their supervisors similarly assessed them, but when looking at the data, they noticed that the servants had a 49,5% lower performance and the bricklayer 69,6% lower performance compared to non-disabled workers completing similar tasks. This difference could be attributed to multiple factors. There could be a decrease in the functional capacity of the disabled worker, or they could make more errors. The study also compared absenteeism between the two groups. Disabled workers were more absent compared to their non-disabled colleagues.

2.3 Contributions to literature

Despite existing research comparing learning model performance, there's a gap in its application to workers with disabilities. As workers with autism or ADHD are more likely to have a learning disability, we cannot assume that the best learning models are still highly-performing when applied to workers with a disability. Furthermore, a physical disability can also hinder the performance of workers and therefore their learning curve. Consequently, in this paper, the performance of the different learning curves are compared using data of workers with a disability. For this, we have applied the same methodology as Nembhard and Uzumeri (2000).

Only the paper of Pooley and Bump (1993) combined the concepts of learning curves and workers with a disability. However, there are limitations to Pooley and Bump's paper because the study only included workers with a mental disability. Our dataset contains workers with physical disabilities, mental disabilities as well as workers with psychological difficulties. Using learning curves, we can investigate both the learning rate and the output of the workers. This paper will compare the learning rate and the output between a range of disability categories such as mental, physical, and psychological. This analysis is important as, according to our research, there are no other literary records of such a comparison.

3. Problem description

The data for this master's thesis was obtained from WAAK, a social enterprise in Kuurne, Belgium. One of the products the company makes are wiring harnesses, which are used in many products from dishwashers to trucks. These wiring harnesses are produced on 'harness boards'. An example of this can be found in figure 2. For each wiring harness, a worker has to learn how the cables should be rooted. The board helps the worker with this task. Tilindis and al. (2017) also used the production times of wiring harnesses in the estimation of their learning curves.

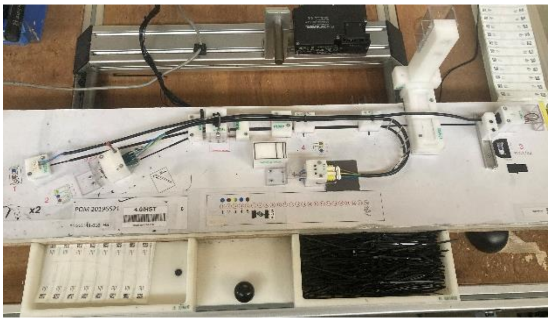

Figure 2: Production of wiring harnesses on harness boards at WAAK.

Every time a wiring harness is finished, the worker scans a barcode. By doing this, an additional row is appended to the enterprise resource planning (ERP) system of the company. For each product, the exact moment of completion is known, as well as the person who made it. The production time can be calculated based on when the previous product was finished by the same worker.

As WAAK is a social enterprise, many of the workers have a disability. If a new employee joins with a disability, it is challenging for the company to identify appropriate work for them. Therefore, the management team at WAAK would like to know the impact of a certain disability on the learning curve and the output of a worker.

At WAAK, a wide variety of wiring harnesses are produced. For comparability, wiring harnesses of equal difficulty have to be considered. In this paper, four different wiring harnesses were selected. These wiring harnesses are used in boilers and have very high production numbers. This was advantageous for two reasons. Firstly, multiple people had already worked on the same wiring harness, permitting a comparison of different people for the same product. Secondly, as production numbers are high, workers produce the items frequently, minimizing the chances of forgetting the previously learned skills. The wiring harnesses had a low difficulty, with an average processing time of two minutes per wiring harness. Workers therefore had on average an output of 30 wiring harnesses per hour. Although the four wiring harnesses are different products, they were very similar to produce. There were only minor differences between the wiring harnesses, e.g. a different electronic connector at the end.

In order to make the learning curves reliable, there is a minimum number of observations necessary for every worker. In this paper, this number is set to 1000. If a worker worked on a product but made less than 1000 products, this learning episode is dropped from the analysis. Some workers made the same cable for multiple years. In this paper, only the first 10 000 production times are considered. After 10 000 units are produced, it is safe to say that the worker has fully learned the task.

4. Finding the best learning curve

In the literature review, multiple learning curves were discussed. Nembhard and Uzumeri (2000) made an extensive comparison of the performance of the different learning curves. However, this comparison was applied to non-disabled workers. To the best of our understanding, there has not been a comparison of learning curves for disabled workers. Therefore, before analysing the impact of a disability on the learning rate we need to know which learning curves are well-suited to disabled workers.

4.1 Methodology

For a good comparison, we based ourselves on the work of Nembhard and Uzumeri (2000). They used three metrics to compare the performance of learning curves: efficiency, stability and parsimony. In this paper, the same metrics will be used.

Efficiency: A learning curve should be flexible enough to fit the data well. The model should be able to work in the following four circumstances: a) positive learning with no previous experience. In this case, the learning curve starts low and is very steep. b) learning with prior experience. In this case, the worker has a transfer of previous experience (in a similar task) that they can use in the new task. Learning is limited. c) positive learning with prior experience. This is a combination of a) and b), where the worker has some previous experience (in a similar task) but still can improve with the new task. d) negative learning, in this case, the performance of the worker regresses. To quantify the fit of the learning curves, the mean-squared error (MSE) will be used. By comparing the average MSE over all learning episodes, the efficiency of each learning curve can be compared.

Stability: A learning curve should work well over all the learning episodes, not just once. A learning curve should be robust. Therefore, the standard error of the MSE will be used to quantify the stability of the learning curve.

Parsimony: Models should be as close to the truth while keeping them as simple as possible. Therefore, the number of parameters that are used by a certain model is important. If a model has a lot of variables, it will fit learning episodes with few data points well. Therefore, there is a preference for models with fewer variables. The number of learning curve parameters is used as a proxy for the parsimony.

Figure 3 contains a flowchart of the methodology in finding the best learning curve for disabled workers. First, the average of every 10 consecutive observations was taken. The production time of every observation is highly volatile. This volatility could result in inaccurate estimations of the learning curve. Conway and Schultz (1959) observed this problem based on production data of planes during the Second World War. They proposed grouping the data and taking the average over multiple consecutive observations to make more robust estimations. Pooley and Bump (1993) made groups of 20 consecutive observations. Nembhard and Uzumeri (2000) took the average of all observations on the same day. In this study, groups of 10 consecutive observations were made. The wiring harnesses studied in this paper have a low level of complexity. On average, a worker needs two minutes to produce a wiring harness, resulting in a daily output of around 250 units. Learning is most pronounced at the task's outset, thus averaging over 10 consecutive observations yields more precise estimates.

Secondly, each learning episode was fitted to all the learning curves discussed in Section *2. Literature review*. This was done with the scipy.optimize.curve_fit function in Python. This function makes use of the non-linear least squares to fit the learning models to the data. The initial guess was constant over the fitting process. This was based on the average production time of a wiring harness of two minutes.

The initial guess of each learning curve implied that the learning curve would achieve an output of 30 units per hour after a few hundred units. This performance was realistic for the worker to achieve.

Thirdly, the goodness of fit of each learning model on every learning episode was calculated with the aid of the MSE.

Fourthly, the average MSE and the standard deviation on the MSEs was calculated for every learning model over all learning episodes.

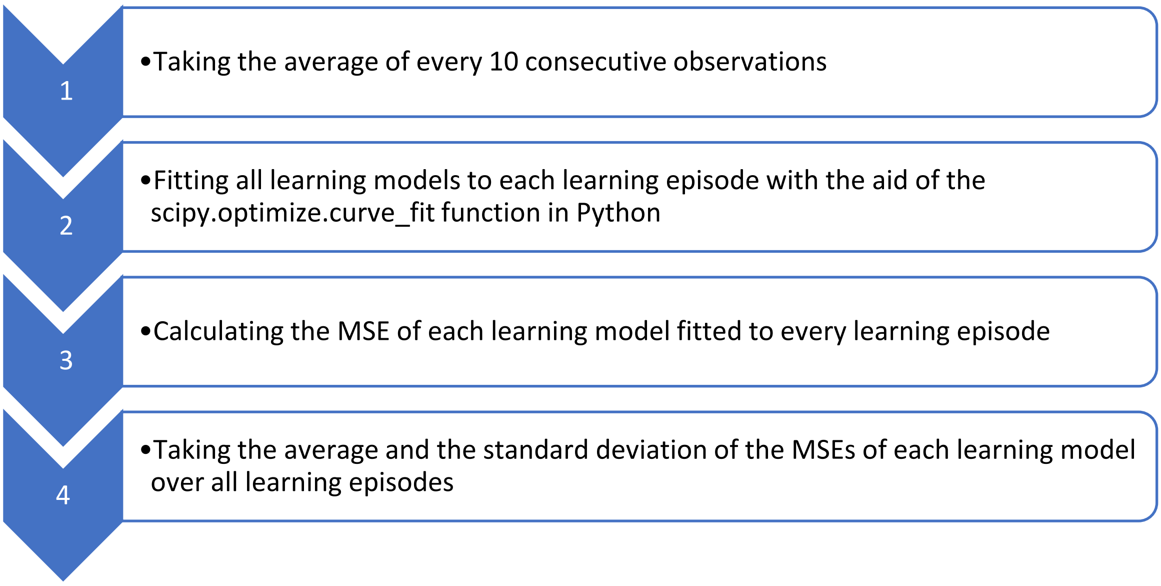

Figure 3: The methodology in finding the best learning curve.

Based on research, we expect that the hyperbolic model with three parameters and the exponential model with three parameters will perform well. In Nembhard and Uzumeri's paper (2000), the Knecht's learning curve and Levy's learning curve performed poorly. We expect that the log-linear model and its modifications will perform better than the hyperbolic model with two parameters and the exponential model with two parameters, but will not achieve the same level of performance as the hyperbolic model with three parameters and the exponential model with three parameters.

At WAAK, all workers receive the same training before starting the production of wiring harnesses. The hyperbolic model with two parameters and the exponential model with two parameters make the assumption that the worker does not have previous experience. This assumption is not valid on our data. Therefore, we expect that these two models will demonstrate lower performance compared to their three-parameter counterparts. However, as all workers receive the same training, one can state that p can be fixed over all workers. Based on empirical tests, p=50 provided a great fit for the data. Therefore, we introduce two modified versions of the hyperbolic and exponential model, as seen in equation (13) and (14). We expect that these will perform better compared to the hyperbolic model with two parameters and the exponential model with two parameters, although having the same number of parameters. However, it is expected that they will not perform as well as the hyperbolic model with three parameters and the exponential model with three parameters.

$$y = k * \left[\frac{x + 50}{x + 50 + r}\right] \tag{13}$$

$$y = k * \left[1 - e^{-\frac{x + 50}{r}}\right] \tag{14}$$

4.2 Results

Table 1 summarizes the results of the analysis. This table contains a column for the efficiency, as well as the stability and the parsimony. When looking purely at the efficiency, the Knecht's learning curve performed best, followed by the hyperbolic model with three parameters and the Stanford-B model. The Levy's learning curve is the worst model when looking at efficiency, stability and parsimony. When comparing the stability of the models, the standard deviation of the MSE is considered. Again, the Knecht's learning curve performs best, closely followed by the hyperbolic model with three parameters and the Stanford-B model. All these models have three parameters. When reducing the parsimony to two, the log-linear model performed best. The hyperbolic model with three parameters and p=50 and the exponential model with three parameters and p=50 outperformed their two parameter counterparts in terms of efficiency and stability. The hyperbolic model with three parameters and the log-linear model are comparable in terms of efficiency and stability. When looking at models with a parsimony of four, it is safe to say that the additional parameter does not improve the fit of the model.

Model	Form	Efficiency $\hat{\mu}_{MSE}$	Stability $\hat{\sigma}_{MSE}$	Parsimony, Number of parameters
Knecht	$y = y_1 * x^b * e^{c*x}$	114,24 (+0%)	212,72 (+0%)	3
Hyperbolic-3	$y = k * \left[\frac{x+p}{x+p+r}\right]$	115,08 (+0.7%)	212,82 (+0%)	3
Stanford-B	$y = y_1 * (x+B)^b$	115,26 (+0.9%)	212,93 (+0.1%)	3
Plateau	$y = C + y_1 * x^b$	115,45 (+1.1%)	213,20 (+0.2%)	3
S-curve	$y = y_1 * [M + (1-M) * (x+B)^b]$	115,52 (+1.1%)	214,49 (+0.8%)	4
Pegels	$y = A * a^{x-1} + b$	116,07 (+1.6%)	216,56 (+1.8%)	3
Log-Linear	$y = y_1 * x^b$	116,16 (+1.7%)	213,66 (+0.4%)	2
Jaber and Guiffrida's LC (2004)	$y = \frac{y_1}{1-b} * x^{1-b}$	116.22 (+1.7%)	213,65 (+0.4%)	2
Hyperbolic-3 with p = 50	$y = k * \left[\frac{x+50}{x+50+r}\right]$	116,22 (+1.7%)	214,00 (+0.6%)	2
DeJong	$y = y_1 * [M + (1-M) * x^b]$	116,51 (+2.0%)	213,92 (+0.6%)	3
Exponential-3	$y = k * \left[1 - e^{-\frac{x+p}{r}}\right]$	117,72 (+3.0%)	214,73 (+0.9%)	3
Exponential-3 with p = 50	$y = k * \left[1 - e^{-\frac{x+50}{r}}\right]$	117,84 (+3.1%)	217.07 (+2.1%)	2
Hyperbolic-2	$y = k * \left[\frac{x}{x+r}\right]$	119,36 (+4.5%)	217,57 (+2.3%)	2
Exponential-2	$y = k * \left[1 - e^{-\frac{x}{r}}\right]$	122,13 (+6.9%)	220,01 (+3.4%)	2
Levy	$y = \left[\frac{1}{\beta} - \left(\frac{1}{\beta} - \frac{x^b}{y_1}\right) k^{-kx}\right]^{-1}$	125,49 (+9.8%)	222,15 (+4.4%)	4

Table 1: The MSE of the different learning models.

4.3 Discussion

In our test, the Knecht's learning curve performed best. Remarkably Nembhard and Uzumeri (2000) found that this model was the worst performing model in their evaluation. The Knecht's learning curve is a modification of the log-linear model to better cope with long production runs (Knecht, 1974). The data of Nembhard and Uzumeri consisted of more than 68 000 observations of 3 874 workers. This implies that there were on average 17,55 data points for every worker. In this paper, there were only 84 learning curves, but on average the learning curves consisted of more than 500 data points. At WAAK, workers have a low turnover rate, which is in line with Pooley en Bump (1993). This could explain the long production runs for every worker. This difference in data structure is probably the reason why the Knecht's learning curve performed well in this paper, but rather poorly in Nembhard and Uzumeri's paper (2000). There could be a second explanation why the Knecht's learning curve outperforms all other models. Because of its mathematical formulation, it is possible to fit a learning curve that initially experiences an increase in performance and in the end a decrease in performance. From a rational point of view, it is not logical that the performance of a worker starts decreasing. However, for people with a disability, this is a possibility. Workers with a psychological vulnerability can have difficulties, impacting their performance. Workers with a muscle disease can experience pain after long production runs. The other models cannot fit this decrease in performance after an increase. They assume that the worker is continuously learning and/or converging to an asymptote.

The second-best model was the hyperbolic model with three parameters. Previous research has shown that it is a great model. It was the best model in the paper of Nembhard and Uzumeri (2000), both in terms of efficiency and stability. Anzanello and Fogliatto (2007) found that the hyperbolic model with three parameters is more robust than the exponential model with three parameters. Therefore, we can conclude that the hyperbolic model with three parameters is still a reliable model for workers with a disability.

In terms of efficiency, the Stanford-B model comes third. The Stanford-B model is an adaptation of the log-linear model that incorporates previous experience. At WAAK, all workers get training before assembling wiring harnesses. A model that can incorporate this previous experience performs better. One can see the log-linear and its modifications (apart from the Levy's learning curve) have a similar performance.

The hyperbolic model with two parameters and the exponential model with two parameters perform not as well as the other models. These models assume that the worker has no experience. As mentioned previously, at WAAK, this assumption does not hold. When the value of p was set fixed equal to 50, the performance of the hyperbolic and exponential model drastically increased and made them competitive to the other models. The Levy's learning curve performed the worst in our analysis. Although based on a log-linear model, it had difficulties fitting the data. Nembhard and Uzumeri (2000) also found it one of the worse performing models in their analysis.

When looking at the stability of the models, the Knecht's learning curve and the hyperbolic model with three parameters perform best. In Nembhard and Uzumeri's analysis (2000), the hyperbolic model with three parameters also had the best stability, whereas the Knecht's learning curve had the worst stability. The big difference in stability with the Knecht's learning curve is probably related to a better fit of the data on the longer production runs of disabled workers. The log-linear model and their modifications perform reasonably well. The stability between the models is again comparable, and the Stanford-B model is again the best. The hyperbolic model with two parameters, the exponential model with two parameters and the Levy's learning curve are less stable. This is again related to the false assumption of no previous experience and the bad fitments of the Levy's learning curve. Setting p = 50 improved the stability of the hyperbolic and exponential model.

Based on our findings, the most adequate model has to be selected for analysis in Section *5. Impact of a disability on learning*. The Knecht's learning curve performed best in our analysis, however the parameters are much harder to interpret compared to the other learning models. The hyperbolic model with three parameters performed similarly to the Knecht's learning curve, but with more explainable parameters. Even though the model only has three parameters, when doing the analysis, we noticed that the model was sometimes overfitting the data. This resulted in unrealistic values for k, p and r. Therefore, a model with a lower parsimony should be selected, for example, the log-linear model. This model would be less likely to start overfitting. The parameters of this model are y_1, which refers to the time the workers produce the product for the first time, and b, the learning rate. y_1 is very volatile between different workers. As workers with a disability have a low turnover rate (Pooley and Bump, 1993), it is more useful to look at long-term performance. However, with the log-linear model, the processing time per unit of the log-linear model will always converge to zero in the long run. Although it could certainly be useful for comparing the learning rate, the log-linear model performs less well for long production runs (Knecht, 1974). The Jaber and Giuffrida's learning curve (2004) is a variant on the original log-linear learning curve, and consequently does not have an asymptote. The hyperbolic model with three parameters and with the value of p set fixed to 50 had a similar performance as the log-linear model, but it did not start overfitting compared to the standard hyperbolic model with three parameters. Furthermore, this model has an asymptote in the long run. Therefore, it can be concluded that this is the most appropriate model to use in Section *5. Impact of a disability on learning.*

5. Impact of a disability on learning

Based on our findings in the previous Section, we use the hyperbolic model with three parameters and p=50 to assess the impact of a disability on learning and production output. The workers are categorized according to their disability and the parameters are compared between the different disabilities. We will make use of a Kruskal-Wallis test in order to verify if these differences are significant.

5.1 Methodology

To see the impact of a disability, workers with similar disabilities were grouped. As every worker is different and every disability is unique, this clustering process was not easy. This was done in collaboration with the social enterprise WAAK. Four groups were formed: workers with a cognitive disability, workers experiencing psychological challenges, workers with disabilities affecting the upper body and workers with disabilities affecting the lower body. This decision was also based on the *Classification of Functioning Disability and Health* of the World Health Organization (World Health Organization, 2001). It is a framework to describe and classify health and health-related states. Categories b100-b199 focus on mental functions. We divided this into attention and cognitive functions (b110, b164) and emotional & personality functions (b152, b152). These workers were put into groups of workers with a cognitive disability and workers experiencing psychological challenges respectively. Categories b210 – b299 are related to sensory function and pain. Categories d140 – d499 are related to mobility. Wiring harness production requires good hand-eye coordination. The sensory function the eyes (b210) and the mobility function of the arm (d445) are therefore important. These workers were therefore categorised in the groups of workers with a disability affecting the upper body. Workers who had a difficulty with walking (d450) and pain in the back (b28013) were put in the category workers with a disability affecting the lower body. As all workers produce wiring harnesses while seated, this mobility function will not hinder their working capabilities. Table 2 describes every group with the disability of the workers.

Workers with a cognitive disability	Includes 2 individuals with a cognitive disability Includes 1 individual with autism Includes 1 individual with autism and ADHD Includes 1 illiterate individual Includes 1 individual with concentration difficulties
Workers experiencing psychological challenges	Includes 12 individuals experiencing psychological vulnerability Includes 3 individuals experiencing significant stress Includes 2 individuals dealing with anxiety Includes 2 individuals facing a challenging home situation Includes 2 individuals who are highly active in group settings Includes 1 individual struggling with addiction Includes 1 individual who tends to be withdrawn in group settings Includes 1 individual diagnosed with borderline personality disorder
Workers with a disability affecting the upper body	Includes 3 individuals with muscle-related conditions Includes 3 individuals with a shoulder issue Includes 2 individuals experiencing visual impairments
Workers with a disability affecting the lower body	Includes 9 individuals with back issues Includes 2 individuals who use a wheelchair Includes 2 individuals with foot related problems Includes 2 individuals with leg issues Includes 1 individual with a knee problem

Table 2: The four groups of disabilities.

It is important to note that some workers had more than one disability and were therefore present in more than one group. However, this was only the case with a minor number of workers. For some learning curves used in Section *4. Finding the best learning curve,* their disability was not known because the worker had left the company. These learning curves had to be dropped in the analysis here. This effect was rather limited, as turnover rates are low in the company.

Table 3 shows the number of disabled workers per category per product. One can note that there are a lot of learning curves for workers with psychological challenges. Some workers worked on more than one product. The four products are similar in terms of production process and difficulty.

Product number	1	2	3	4	Total
Cognitive disability	2	1	2	2	7
Psychological challenges	10	8	9	9	36
Disability affecting the upper body	5	4	5	4	18
Disability affecting the lower body	5	4	4	3	16
Total	22	17	20	18	77

Table 3: Number of disabled workers per product.

In Section *4. Finding the best learning curve*, it was concluded that the hyperbolic model with three parameters, with the value of p set fixed to 50, was the most suitable model for comparing the learning rate and the output between different groups with similar disabilities. This model is represented again in equation (15). y refers to the units per hour after x units are produced. k is the asymptote and refers to the performance of the worker in the long run, once they have finished learning. A worker with a higher k implies that they can work faster. r refers to the learning rate of the worker. A lower (but positive) value of r implies that the worker is learning faster. A negative value of r implies that they are forgetting instead of learning.

$$y = k * \left[\frac{x + 50}{x + 50 + r}\right] \tag{15}$$

We expect that workers with a disability affecting the upper body will have a normal learning rate and that their performance, in the long run, is lower. Their disability can hinder the speed at which they work. Regarding workers with a disability affecting the lower body, we would expect their learning rate and output to be similar to a non-disabled worker. All workers are seated during the production process. Therefore, it is not expected that their disability will hinder their working performance.

From our literature review, one would expect that workers with a cognitive disability have a lower learning rate compared to non-disabled workers. People with autism are more likely to have a learning disorder. However, Pooley and Bump (1993) found that in their analysis, workers with intellectual disabilities do not have a lower learning rate compared to non-disabled workers. Pooley and Bump made use of the log-linear model in their analysis, so it is difficult to make a conclusion on long-term performance. The initial time of a worker with a disability is higher compared to a non-disabled worker. Regarding workers with psychological challenges, we expect volatile learning rates and volatile final performance, as these workers are less stable.

Figure 4 represents a flowchart of the methodology. First, we assign all the workers to the correct group corresponding to their disability. Secondly, we fit the learning episodes to the hyperbolic model with three parameters (with p set fix to 50). Thirdly, the fitted values of k (output in the long run) and r (learning rate) are visualised with the aid of a scatterplot. Finally, a Kruskal-Wallis test is used in order to check if the differences in k and r are significant between the different groups of disability. We opted for the Kruskal-Wallis test as this is a non-parametric test in contrast to an ANOVA test.

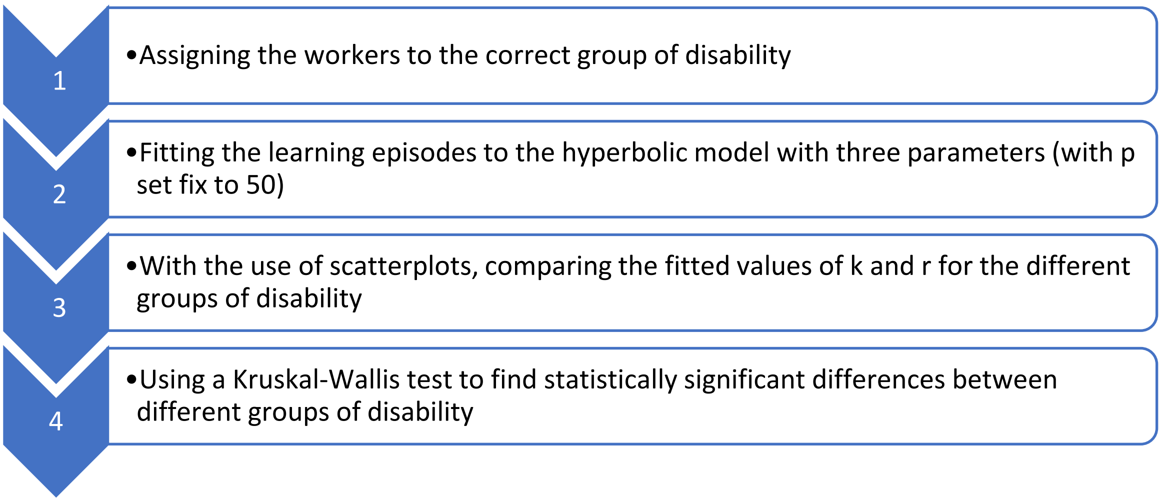

Figure 4: The methodology in analysing the impact of a disability on learning.

5.2 Results

Figure 5 and 6 contain a scatterplot of the fitted values of k (output in the long run) and r (learning rate) respectively. Both figures contain four individual plots. They refer to the four different products in this analysis. These four different wiring harnesses are very akin to each other, with a similar level of complexity to produce. Every dot represents an individual worker. The green dots refer to workers with a disability affecting the upper body, the orange dots refer to workers with a disability affecting the lower body, the red dots refer to workers with psychological challenges and the blue dots refer to workers with a cognitive disability. The median of every group is marked with a ‘x’. We opted for the median and not the mean as this is prone to outliers.

Figure 5 contains the scatterplots of the values of k. k refers to the output when fully learned. A higher value of k implies a worker produces more units per hour after they had finished learning. One can state that workers with a disability affecting the lower body have on average the highest output once they had fully completed learning. Workers with a disability affecting the upper body have second highest output in the long run, followed by the workers with psychological challenges. Workers with a cognitive disability have on average the lowest output after they had finished learning. One can also note that there is a lot of variance between the different workers, especially in between the workers with psychological challenges and workers with a disability affecting the upper body.

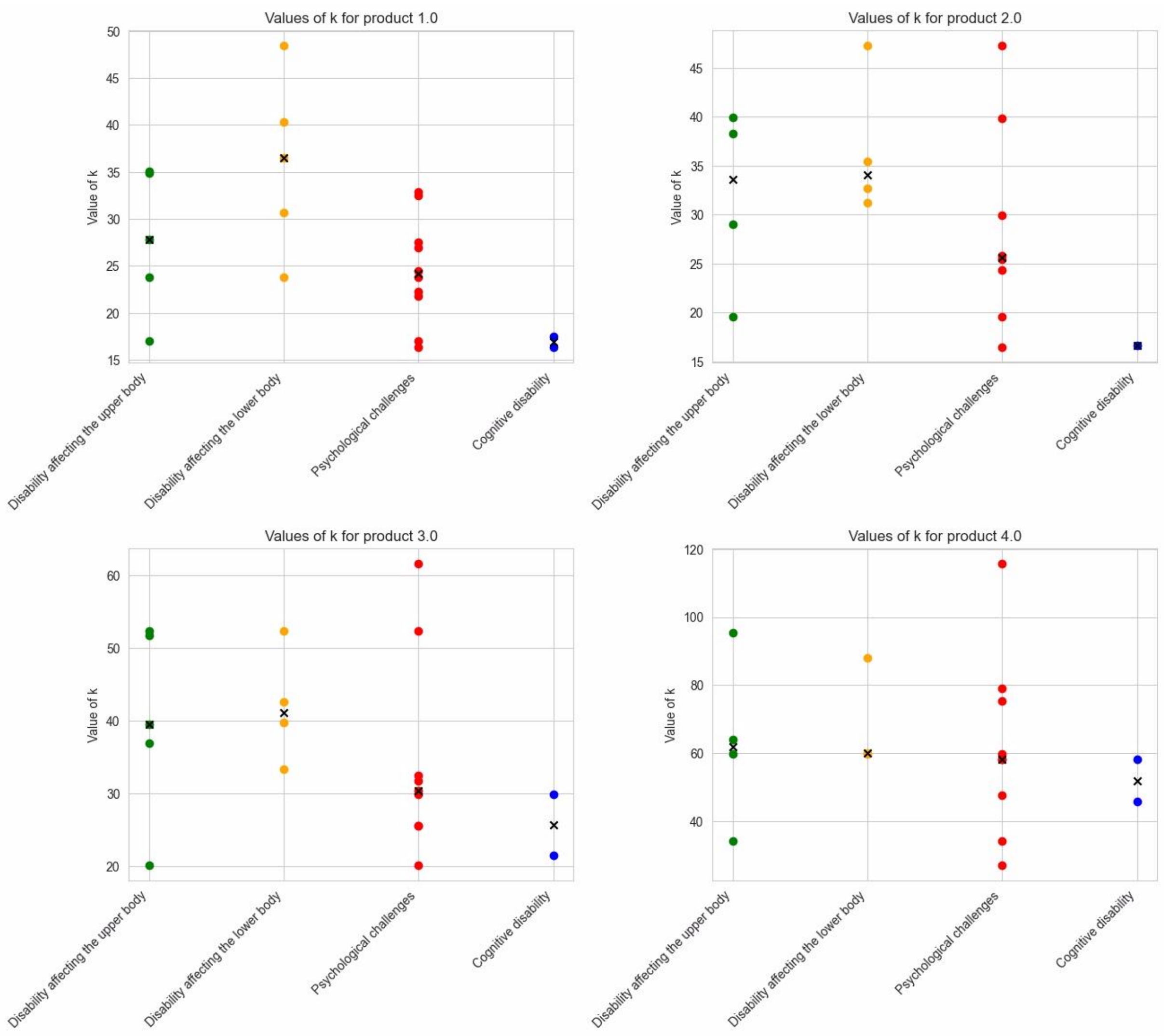

Figure 5: Scatterplots of k for the four different products.

Figure 6 contains scatterplots of the value of r. r refers to the learning rate. A low, but positive, r refers to a fast learning person. A high r refers to a slow learning worker. A negative r refers to a employee who is forgetting. One can see that for every product, there are fast learning workers and slow learning workers in every group of disability. Every group of disability also has at least one worker that had a negative learning rate. Therefore, it is hard to see a relationship between the type of disability and the learning rate. There is also considerable variation within the different groups, this is the case for all disabilities.

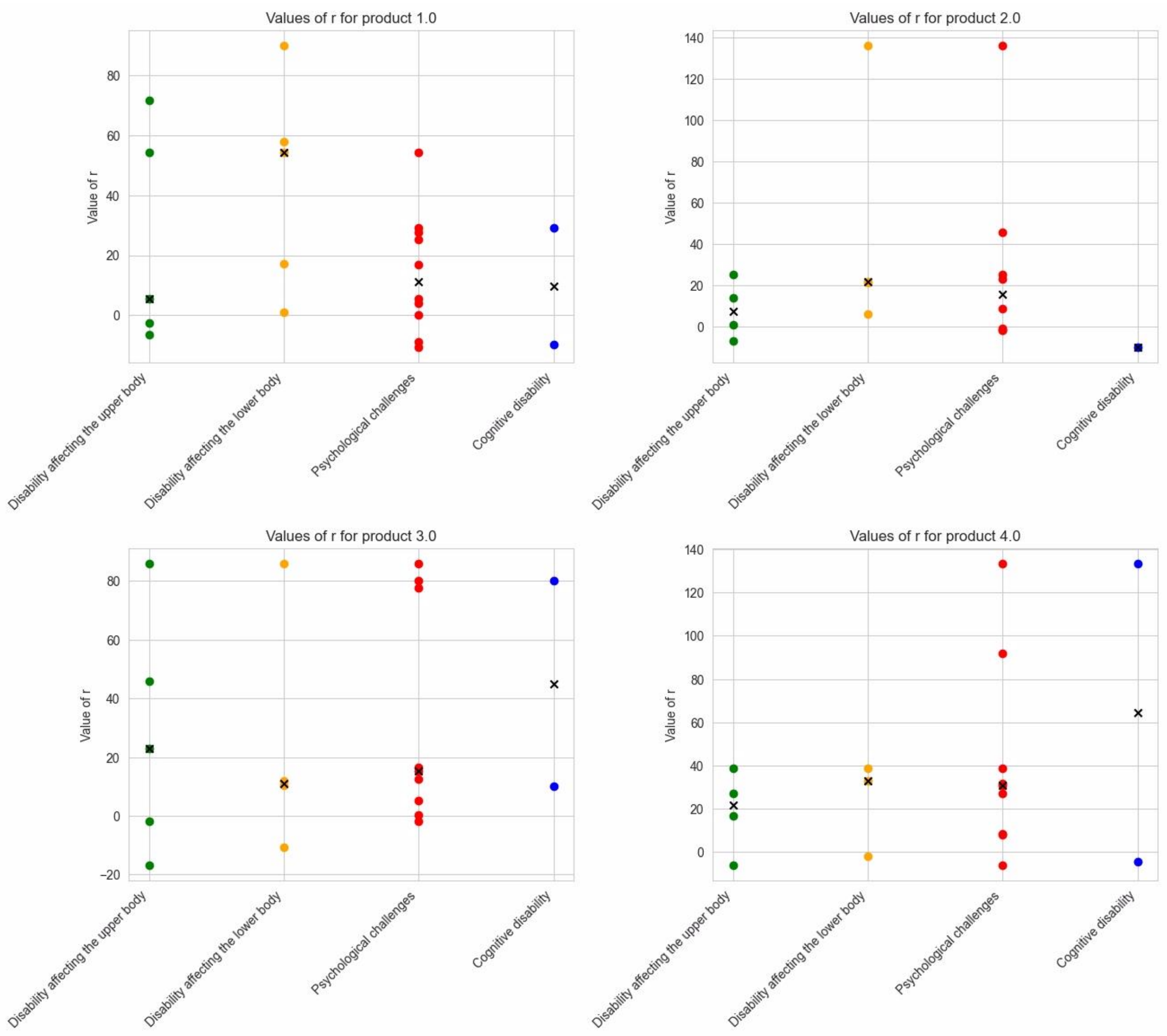

Figure 6: Scatterplots of r for the four different products.

Figure 7 shows the learning episodes of the workers on product one. The figure contains four plots, every plot refers to a certain disability. Every curve on those plots is one individual worker. The horizontal axis shows is the cumulative number of units produced by the worker. The vertical axis shows the output of the worker. The vertical axis ends at 4 000 units, as we can observe that most workers start to reach their asymptote. One can notice that some curves stop short of 4 000 units, as not all workers achieved this production number. However, in this analysis, all workers produced at least 1 000 units. One can notice that the workers with a cognitive disability (the blue curves) on average have the lowest output. Workers with psychological challenges (the red curves) have the second lowest output. As this group is numerous, this is reflected in the high number of red learning curves. Workers with a disability affecting the lower body (the orange curves) have on average the highest output, followed by the workers with a disability affecting the upper part of the body (the green curves). Here again, we cannot see a relationship between the type of disability and the learning rate (the steepness of the learning curves). The plots for products 2, 3 and 4 are very similar. We would like to refer to appendix *A. Learning curves for product 2, 3 and 4* for more detail.

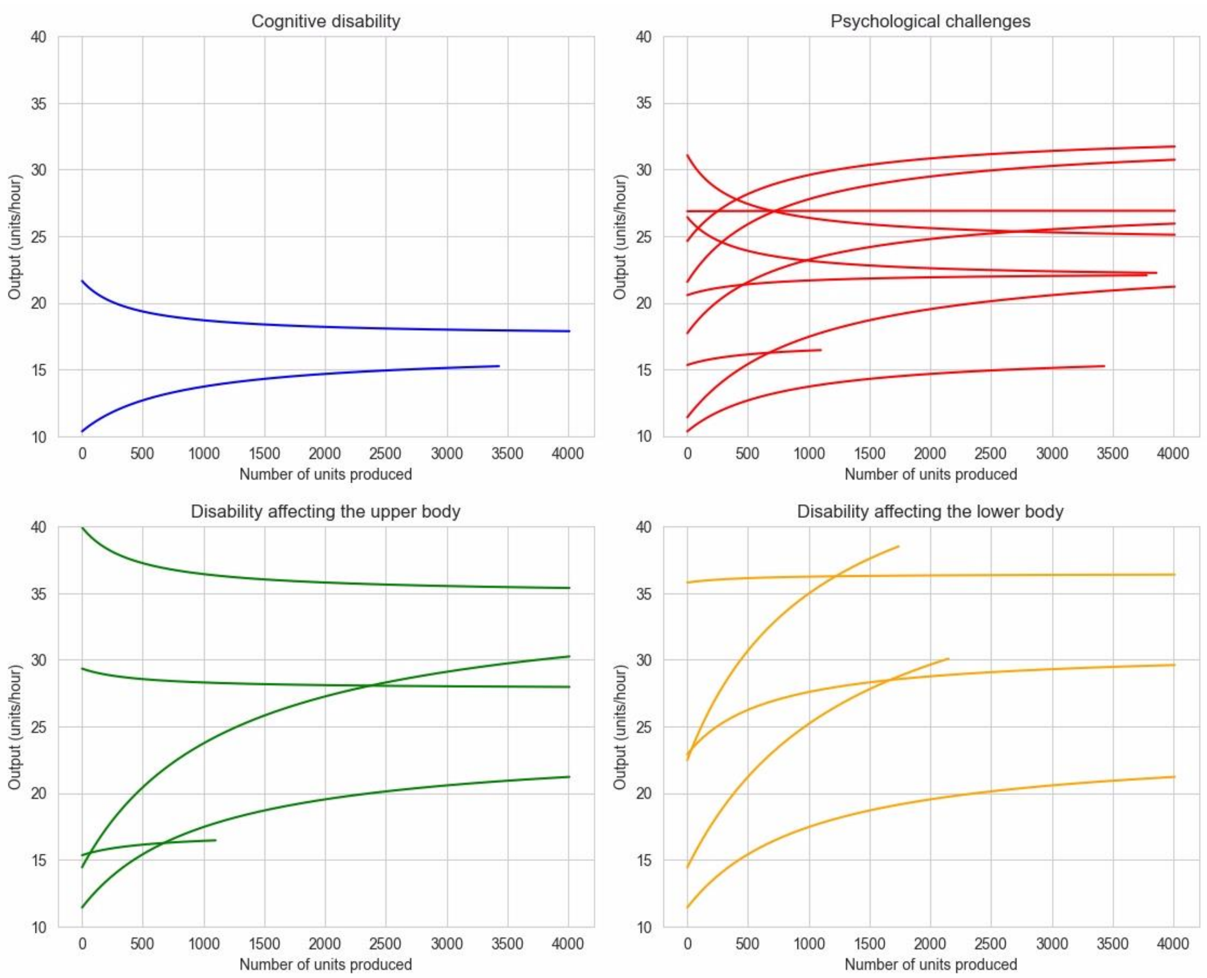

Figure 7: Learning curves for the different disabilities for product 1.

To verify if the differences in output and learning rate are significant, a Kruskal-Wallis test was used. The results of the Kruskal-Wallis test for k can be found in table 4. The H-statistic of the test is 7,989 with a corresponding p-value of 4,6%. Therefore, one can conclude that the impact of a disability on k (output when fully learned) is significant.

	H-statistic	p-value
Kruskal-Wallis test	7,989	0,046

Table 4: Kruskal-Wallis test results for k.

In table 5, the average output of a worker per category is given. Workers with a disability affecting the lower body have the highest average output of 44 units per hour. They are followed by the workers with a disability affecting the upper body, with an average output of 40 units per hour. Workers with psychological challenges and workers with a cognitive disability have a lower output of 37 and 29 units per hour respectively.

	Average output
Workers with a cognitive disability	29
Workers with psychological challenges	37
Workers with a disability affecting the upper body	40
Workers with a disability affecting the lower body	44

Table 5: The impact of a disability on k.

Similar to the previous test, the Kruskal-Wallis test can be used to analyse the impact of a disability on the learning rate as shown in table 6. However, it is important to note that the interpretability of r is not linear. A lower value implies a faster learning worker. However, when r becomes negative, the worker stops learning and begins forgetting. The test does not take into account this non-linear effect. As the number of negative learning episodes is low, we believe that this effect will be limited. The Kruskal-Wallis test has a H-statistic of 1,788 with a corresponding p-value of 0,618. This implies that the impact of a disability on the learning rate is not significant.

	H-statistic	p-value
Kruskal-Wallis test	1,788	0,618

Table 6: Kruskal-Wallis test results for r.

Table 7 shows the average r for every group of disability. Workers with a disability affecting the upper body have the lowest average learning rate of 20. Therefore, they learn the fastest. They are followed by workers with psychological challenges, with an average learning rate of 29. Workers with a cognitive disability and workers with a disability affecting the lower body have a learning rate of 33 and 36 respectively. Consequently, they learn the slowest.

	Average learning rate
Workers with a cognitive disability	33
Workers with psychological challenges	29
Workers with a disability affecting the upper body	20
Workers with a disability affecting the lower body	36

Table 7: The impact of a disability on r.

5.3 Discussion

From our results, one can better understand the impact of a disability on learning rates and output. Workers with a disability affecting the lower body have the highest production output. As all workers execute their tasks seated, their disability does not hinder their productivity. Workers with a disability affecting the lower body will therefore perform similarly to workers without a disability. As the tasks involve manual labour, it is not surprising that workers with a disability affecting the upper body have a lower output. We also expected this based on our literature (Guimaraes et al, 2016). The impact of psychological challenges on the worker performance is important. These workers have a much lower output. Workers with a cognitive disability have the lowest productivity. Pooley and Bump (1993) concluded that the performance of a mentally disabled worker after a long production run is similar to the performance of a non-disabled worker after a much shorter production run. Based on our hyperbolic model, we could conclude that, after a long production run, workers with a disability affecting the lower body still outperformed workers with a cognitive disability. These results were also statistically significant.

Regarding the output of the workers with a disability affecting the upper body and workers with psychological challenges, one can notice high variations in the point estimation plots. Workers with psychological challenges often have more difficult periods, hindering their performance. This can explain the high variation in output for different workers. The group with a disability affecting the upper body is diverse. It contains workers with visual impairments, workers with muscle-related conditions and workers with shoulder issues. This high variation of disability can explain the high variation in production output.

When discussing the impact of a disability on the learning rate, it is less clear. The results are not significant, concluding that workers with a cognitive disability or psychological challenges have a similar learning rate to workers with a physical disability. In the data, there was a wide variety of learning rates. While most workers had positive learning rates, some workers had a negative learning rate and saw a decrease in performance over time. It is impossible to say if this was linked to their disability or if the workplace is not designed for their specific disability. Because of the big variety in learning rates, the Kruskal-Wallis test results were not significant. Pooley and Bump (1993) showed in their research that the learning rate of a mentally disabled worker was comparable to a non-disabled worker.

Finally, it is important to make a short note on cost effectiveness. Pooley and Bump (1993) state that hiring disabled workers is financially beneficial for the company, as employers get a job credit for employing disabled workers. This is also the case in Belgium. These benefits are dependent on the disability. A company receives more financial initiatives for hiring a severely impaired worker compared to a mildly disabled worker. One would expect that the severity of a disability would directly impact the worker's output. In our data, we did not find that workers with a more severe disability performed less well. However, as this falls out of the scope of our research, we would like to refer to the appendix *B. the severity of the disability and the output of the worker* for a more in depth analysis.

6. Limitations and further research

If workers do not complete the task for a while, they will start to forget previously learned skills. Although there are models that predict forgetting, this was not taken into account in this paper. Nevertheless, the effects of forgetting were limited by the high production numbers of the products. The four selected products are frequently produced, therefore the workers have little opportunity to forget. In the dataset, there were a few examples of negative learning. Although it is not logical for a worker to forget skills while continuously working on the same product, it is plausible that the repetitive task impacts motivation which impacts worker performance (Shahzadi et al, 2014).

Although the dataset of the social enterprise workshop was very extensive, a lot of products were only produced occasionally and only by a few workers. These products could not be included in the analysis, as multiple workers had to work on the same product for good comparison. There were also learning curves of workers who stopped working at the company. As the disability of the person was not stored in the ERP system, it was impossible to know which category of disability they belonged to and therefore they were dropped from the analysis. Although some results were significant, more data would imply a higher power of the Kruskal-Wallis tests.

Another weakness is that the production times are not stable throughout the day. Based on an ANOVA test, workers work slower in the afternoon compared to the morning. Just before the lunch break the output decreases as well. The workers in the analysis of Nembhard and Uzumeri (2000) were paid per unit. Therefore they were always financially motivated to produce products of good quality as fast as possible. This was not the case at WAAK.

At WAAK, all workers do their task seated. Workers with a disability affecting the lower body still have the dexterity to assemble products like normal workers. However, workplace design is very important. Suppose there is a task that requires the worker to alternate between seating and standing. Then the workplace should be designed that this task is also feasible for a worker with a disability affecting the lower body. For example, robots could be used to assist him.

A final limitation is the grouping of disabilities used in Section *5. Impact of a disability on learning.* Although a lot of effort was put into making four distinct groups, there is still a lot of variation within the groups. If more groups were made, there would be less workers in every group and the Kruskal-Wallis test would have less power. Further research could be completed in which the same experiment is repeated, but with more workers and with more groups in order to minimalize the differences of people within a group.

In this study, we focused on four wiring harnesses with limited complexity. We suggest further research to try the same analysis on other products. Furthermore, it would be interesting to try the examination on products with a higher level of difficulty and verify if the same results still hold.

7. Conclusion

As seen in the literature review, learning curves have already been widely used. They can be used to describe both organizational learning and individual learning. Although a comparison of individual learning curves was already performed in the past, as far as we are aware, this had not happened yet on workers with a disability. For this comparison, data was used from WAAK, a social enterprise in Belgium. 84 learning episodes were analysed in the production of wiring harnesses. The Knecht's learning curve performed best in terms of efficiency and stability, followed by the hyperbolic model and the Stanford-B model. Next, the impact of a disability on the output and the learning rate was analysed. For this, the workers were classified into four categories: workers with a cognitive disability, workers with psychological challenges, workers with a disability affecting the upper body and workers with a disability affecting the lower body. As the parameters of the Knecht's learning curve are hard to interpret, we opted for a hyperbolic model, carefully balancing performance and interpretability. Based on our analysis, we can conclude that disabilities have a significant impact on worker performance. As all workers were seated during the production process, the workers with a disability affecting the lower part of the body were not hindered by their disability and had the highest output. Workers with a disability affecting the upper part of the body had the second highest output, followed by the workers with psychological challenges. These two groups also had a high variance in output between the different workers. Workers with a cognitive difficulty had on average the lowest output. The difference in disability does not have a significant impact on learning rates. Furthermore, we suggest further research to apply this model again with different and more complex products.

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9. Appendix

A. Learning curves for product 2, 3 and 4

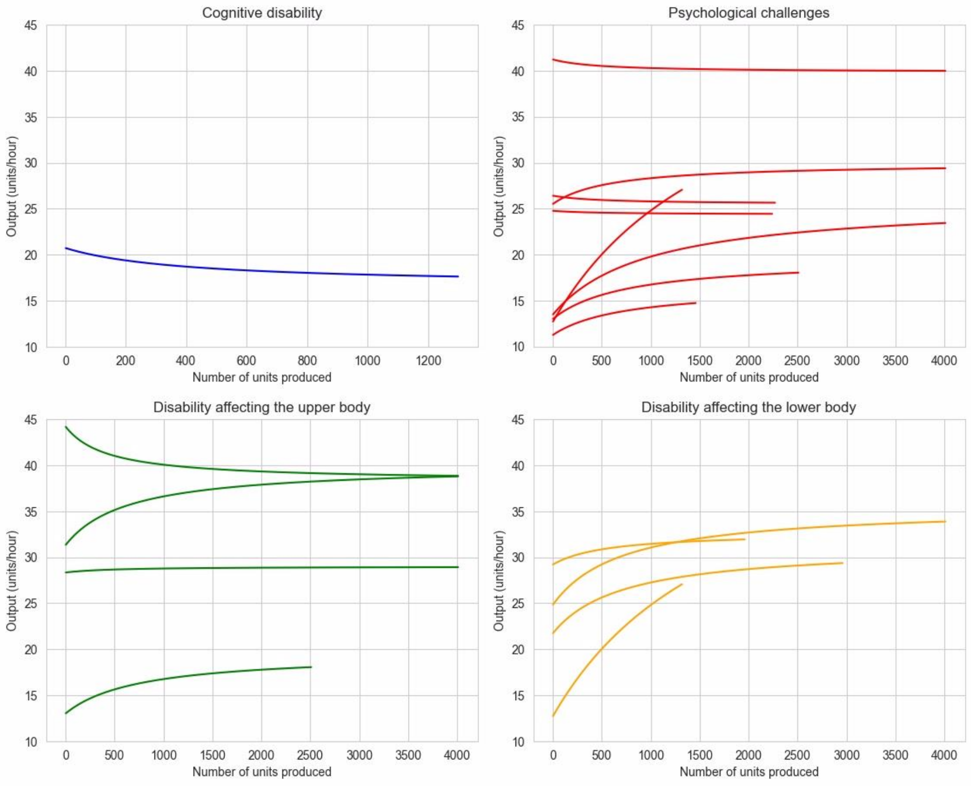

Figure 8: Learning curves for the different disabilities for product 2

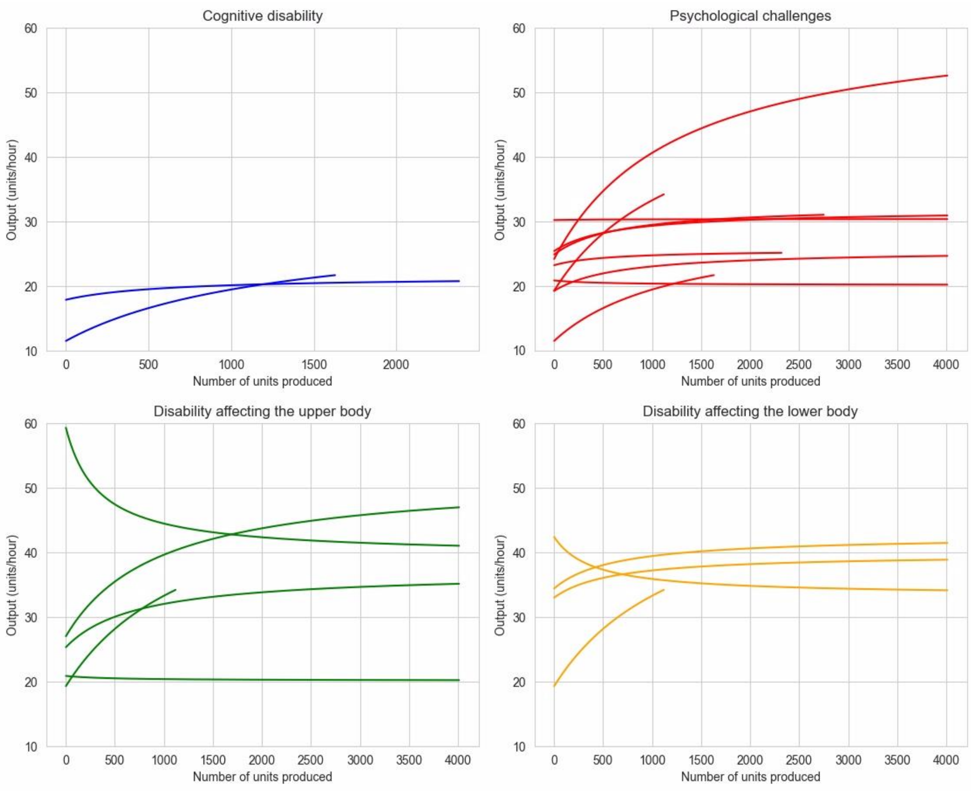

Figure 9: Learning curves for the different disabilities for product 3.

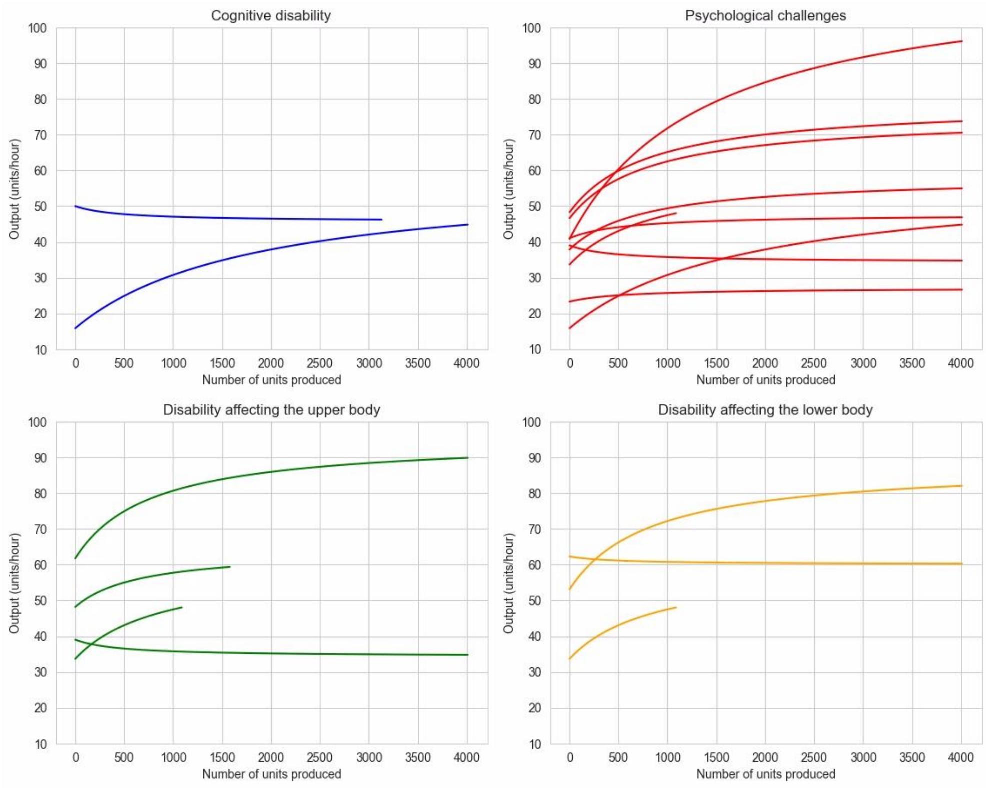

Figure 10: Learning curves for the different disabilities for product 3.

B. The severity of the disability and the output of the worker

In the discussion of Section *5. Impact of a disability on learning*, we mentioned that there is no link between the financial benefits a company receives for engaging a disabled employee and the output of that employee. As this observation is highly relevant but falls out of the scope of the paper. However, we want to elaborate more on this in the appendix.

As mentioned in the paper, the Belgian government provides financial benefits to companies that employ disabled workers. The government does not make a categorization based on a mental or physical disability, but rather on 'mildly disabled', 'moderately disabled' and 'severely disabled' (and some small rest categories). An employer gets more benefits for hiring a severely disabled worker compared to a mildly disabled worker. In our data, the category of the worker was available. There were no workers with a mild disability. Figure 11 shows the individual learning curves for the moderately and severely disabled workers for product 2. The figure is very similar to figure 7, but the curves have different labels. The horizontal axis shows the cumulative number of units produced for every worker. The vertical axis shows the output of the worker. Each curve refers to a worker. The red curves refer to workers with a moderate disability, the blue curves lines refer to workers with a severe disability. One would expect that the moderately disabled workers have a higher output compared to severely disabled workers. However, in the graph this is not visible. Both groups have similar output. This can have multiple explanations. It is possible that the task was equally difficult for moderately and severely disabled workers. Another explanation could be that the categorization of the government is not specifically made for the production of wiring harnesses, and therefore the categorization is not accurate. Figure 12 shows a comparison between the severity of the disability and the output for product 4. Here again, no clear relationship between severity and output is visible.

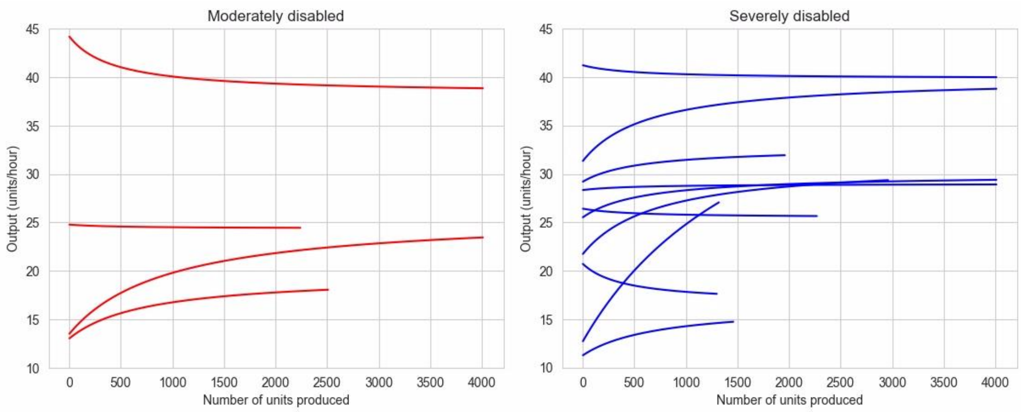

Figure 11: Learning curves for moderately and severely disabled workers for product 2.

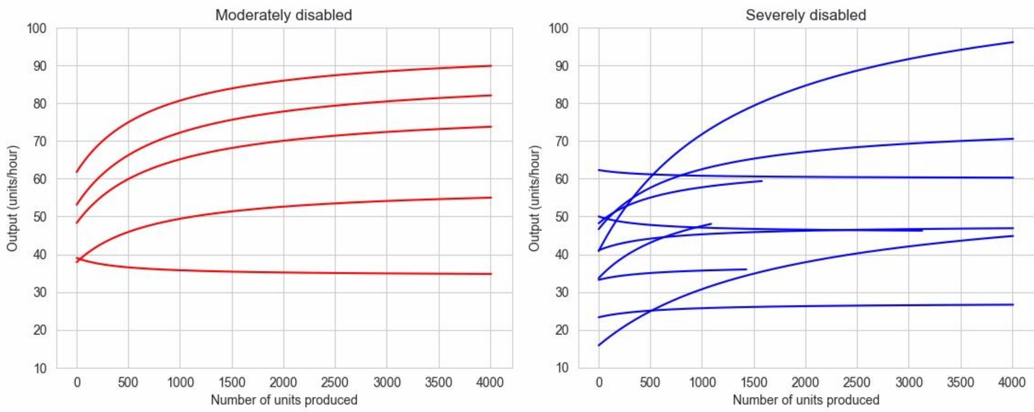

Figure 12: Learning curves for moderately and severely disabled workers for product 4.