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Technical Paper

Assessing the influence of expert video aid on assembly learning curves

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ABSTRACT

Since the introduction of the concept of learning curves in manufacturing, many articles have been applying the model to study learning phenomena. In assembly, several studies present a learning curve when an operator is trained over a new assembly task; however, when comparisons are made between learning curves corresponding to different training methods, unaware researchers can show misleading results. Often, these studies neglect either or both the stochastic nature of the learning curves produced by several operators under experimental conditions, and the high correlation of the experimental samples collected from each operator that constitute one learning curve. Furthermore, recent studies are testing newer technologies, such as assembly animations or augmented reality, to provide assembly aid, but they fail to observe deeper implications on how these digital training methods truly influence the learning curves of the operators. This article proposes a novel statistical study of the influence of expert video aid on the learning curves in terms of assembly time by means of functional analysis of variance (FANOVA). This method is better suited to compare learning curves than common analysis of variance (ANOVA), due to correlated data, or graphical comparisons, due to the stochastic nature of the aggregated learning curves. The results show that two main effects of the expert video aid influence the learning curves: one in the transient and another in the steady state of the learning curve. The transient effect of the expert video aid, where the statistical tests suffer from a high variance in the data, appears to be a reduction in terms of assembly time for the first assemblies: the operators seem to benefit from the expert video aid. As soon as the steady state is reached, a slower and statistically significant effect appears to favor the learning processes of the operators who do not receive any training aid. Since the steady state of the learning curves represents the long term production efficiency of the operators, the latter effect might require more attention from industry and researchers.

1. Introduction

In 1885, Hermann Ebbinghaus proposed the concept of learning curve in the field of the psychology of learning, although the name did not come into use until 1903 [1]. In 1936, Theodore Paul Wright described the effect of learning on production costs in the aircraft industry and proposed a mathematical model of the learning curve [2]. In the 1970s, the learning curve theory was commonly accepted in the airframe industry as a tool for cost estimating [3]. In 1990, Argote and Epple [4] presented a review of learning curves in manufacturing, followed, in 1991, by Badiru [5] with a multivariate learning curve perspective, and by more recent reviews by Anzanello and Fogliatto [6] and Glock et al. [7]. While the use of learning curves was initially dominant in the calculation of manufacturing costs [8], these models have slowly found applications in manufacturing processes [9], in lot sizing problems [10], in inventory models [11], for job scheduling in assembly lines [12], etc. Klenow [13] acknowledged that learning by doing is largely specific to each production technology and used the learning curves to estimate when to update a certain technology in industry, in particular, he noticed that technology updates temporarily decrease productivity. On the same line is the work from Ngwenyama et al. [14] that specifically proposed to use the learning curves to determine when to execute software upgrades to maximize productivity in industry. In assembly, Sebrina and Cakravastia [15] proposed the use of learning curves to investigate the learning rates in automobile assembly lines and deal with technological changes. Anzanello and

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Fogliatto [16] used the learning curves to decide work assignments on mass customized assembly lines. Cohen et al. [17] proposed an optimal allocation of work in assembly lines for lots with homogeneous learning. The number of works applying learning curves in manufacturing applications has become uncountable.

The task of interest for this article is the use of the learning curves to characterize the training of industrial operators [5] over assembly tasks by means of different technologies and methods.

As shown in the related works section, few authors were able to perform at most a common analysis of variance (ANOVA) on assembly learning curves. Using ANOVA (or multiple 2-sample *t*-tests) requires testing the hypothesis on the sample (independence) and the distribution and variance of the residuals of the model. Hypothesis that, if not verified, reduce drastically the quality of the analysis [18,19]. Additionally, ANOVA allows the comparisons of specific repetitions and it does not consider the overall learning curve.

To the best of the authors' knowledge, since the introduction of the learning curve concept, no work in literature pertaining the training of assembly tasks has attempted a statistical comparison of the learning curves by means of functional analysis of variance (FANOVA). Furthermore, even if videos are considered a standard method for the training of assembly tasks [20–22], a robust statistical analysis of the expert video aid seems to be missing in literature. Thus, the double aim of this work is to introduce FANOVA as a more robust method for the comparison of learning curves and to use it to determine the influence of expert video aid on the assembly time in a simple benchmark assembly task.

An extra outcome of this article is to provide guidance for improving similar analyses in studies about related assembly training and assistance technologies, e.g. virtual, augmented or mixed reality training tools (an exhaustive list can be found in [23]). Presenting statistically significant comparisons over the entire interval of the learning curves is a practice that can produce a better understanding of the influence of any methods that can be modelled by learning curves. Since the literature review showed many of these cases, the solution proposed in this particular study can be easily extended to other applications in manufacturing.

The article is further organized as follows. Related works are presented in Section 2. The research methodology is presented in Section 3. The experimental results are reported in Section 4. Discussions of the results, conclusions and proposals for future works are in Section 5.

2. Related works

This section summarizes several related works pertaining the comparison of learning curves in assembly tasks, relative to any possible technology used to aid the training of the operators.

Hou et al. [24] proposed to use animated augmented reality to cognitively guide the assembly and compared their learning curves (from now on intended as functions of assembly time per repetition, if not specified otherwise) with traditional training methods; however, their statistical comparison of the learning curves over four repetitions relies on ANOVA, a practice that is not guaranteed to work properly with correlated data [18,19] such as the assembly repetitions performed by the same operator.

Hoedt et al. [25] evaluated an elementary virtual training system for manual assembly with learning curves generated over eleven repetitions of real and virtual versions of the same assembly task; even in this case, the comparison is based on a one-way ANOVA between repetitions.

Carlson et al. [26] proposed a similar virtual training system and made comparisons between the real and virtual assembly task repeated as many times as possible in 20 min for each participant. In this case, the comparison of the learning curves was made only graphically, whereas statistical analyses (one way ANOVA) were performed over the results of several tests aimed at assessing the user skills rather than directly comparing the learning curves.

Peniche et al. [27] combined virtual and augmented reality to improve the mechanical assembly training process. In their case, the comparison of two learning curves, done with one way ANOVA, leads to a result of no statistical significance of the difference found.

Pilati et al. [28] proposed an assembly guidance system based on augmented reality and compared the learning rates of two learning curves based on fifteen repetitions of several operators using the augmented reality and the paper-based instructions. In this work, the learning curves comparison is graphically presented and the learning rate comparison is performed without the help of any statistical methods.

Gallegos-Nieto et al. [29] performed an analysis and evaluation of the influence of an haptic-enabled virtual assembly training on real assembly performance. In their work, several experiments were conducted considering three assembly training modes, five assembly tasks with variable levels of complexity and different numbers of parts, using five repetitions to define the learning curves. Their analysis of results, based on one-way ANOVA, shows that the virtual training has a significant effect on the real assembly performance up to the first two or three iterations, depending on the assembly complexity. This is an example of work that fails to assess the long term effect of the virtual training method (i.e. on the tail of the learning curve) because of the lack of power from the statistical tools used: not reaching statistical significance in the tests does not allow to draw precise conclusions on the observed variables.

Adams et al. [30] presented a virtual training method for a manual assembly task and compared learning curves based on five repetitions using a pair-wise Tukey's honest significance test on repetitions one and four. The tests did not show statistically significant differences for many of the combinations presented, namely virtual training with or without haptics feedback and the control run without virtual training. En example of work that could have benefitted from a better statistical analysis of the learning curves.

Another set of examples are works such as the one from Loch et al. [31] that compared video and augmented reality (AR) assembly training methods, but found no statistically significant difference between the two; however, their analysis is not based on learning curves but only on one repetition of the assembly task.

Schuster et al. [32] performed a similar analysis for AR-assisted assemblies. They compared a test group with AR assistance and a control group to whom no assistance is provided. They concluded that the assembly time is shorter with the AR assistance, even though the experimental data in their study was collected over one repetition of the assembly per operator and no statistical analysis was performed over the two experimental groups. A plot of the means and variances was provided, but the graphical method is not reliable without a supporting statistical analysis.

Previous work by de Giorgio et al. [33] has found statistically significant difference between expert aid, non-expert video aid and no aid, by means of two way ANOVA with Box-Cox transformations. Even in this case, on a single assembly repetition per operator. The work highlights the need of improving the learning model and the relative statistical analysis.

In conclusion, the state of the art shows that ANOVA and simple comparisons were used to test the effectiveness of video aid, as much as other digital techniques such as virtual or augmented reality, on learning curves. The disadvantage of ANOVA is that it can evaluate the differences in the learning curves in a specific repetition. If multiple repetitions at the same time are tested, the Bonferroni approach should be used to control the family-wise error; otherwise the likelihood of rejecting the null hypothesis increases. For this reason, using ANOVA to compare two or more curves is not suggested unless only a specific repetition of the experiment is of interest. In this work, we propose a statistical method, FANOVA, that performs the comparisons between two learning curves based on experimental data. The advantage of FANOVA is that it avoids the definition of an *a priori* function to describe the data, such as $y = ax^{-b}$. This is an advantage because the inevitable heterogeneity of the experimental data leads low-quality fitting of the data, and therefore the need for weighted analysis or data transformation which leads to a more complicated interpretation of the results [19].

3. Research methodology

The aim of this research is to present a benchmarking product for the learning curve experiments, produce an expert video aid, prepare and execute the experiments and perform a functional analysis of the obtained learning curves. Each of these operations is presented in the following subsections.

3.1. Locomotive assembly

The benchmarking product selected for the calculation of the learning curves in assembly is the metal locomotive illustrated in Fig. 1. This product is locally manufactured at KTH Royal Institute of Technology in the course MG1016 Manufacturing Technology. The locomotive consists of 21 components (see Fig. 2), including the necessary screws. The locomotive is an interesting benchmarking product for the expert video aid because it has been used for previous studies in assembly [33,34].

3.2. Expert video aid

The video aid is recorded by a researcher who has the necessary expertise to assemble the metal locomotive. The video is made of nine scenes, one for each assembly step. The assembly sequence and the script are presented in Table 1. Each scene begins with a still visualization of all the components and the tools that are needed; then, it shows how to perform the assembly step in exam, from a first-person perspective, in line with the recommendations of Fiorella et al. [35]. In the video, the operation is executed while commented with a clear voice, accordingly to the script.

3.3. Experimental setup

The experimental setup consists of an assembly station on which are present an assembled locomotive for reference (see Fig. 1) and an exploded view of the locomotive on paper (see Fig. 2), in addition to the 21 locomotive components (including the screws) and the necessary tools to assemble them. The tools are two Phillips screwdrivers, a Torx screwdriver, a Pozidriv screwdriver, a hex screwdriver and a wrench. A monitor placed on the assembly station is used to show the expert video aid.

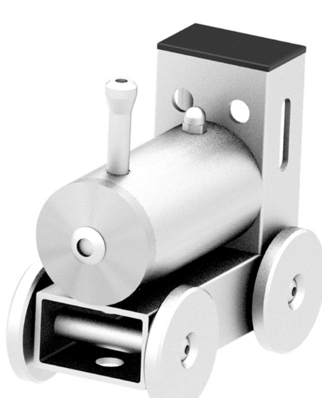

Fig. 1. Metal locomotive rendering from its CAD file.

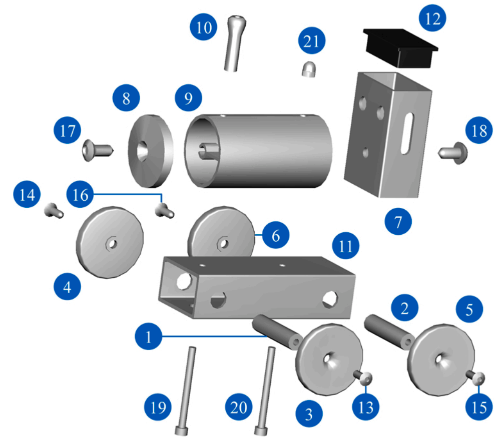

Fig. 2. Locomotive components and their identifiers.

Table 1
Assembly sequence and script for the expert video aid.

Scene	Components	Script
1	8, 9, 17	Insert the nose cone (8) into one of the two sides of the boiler (9). Assemble them using a Pozidriv screw (17) and the Pozidriv screwdriver.
2	7, 12	Insert the roof into the top side of the cabin. Keep the alignment as vertical as possible during the insertion.
3	9, 10, 11, 19	Insert a hex-head screw (19) into the front side hole of the bottom frame (11) and into the boiler (9). Hold the chimney (10) as a bolt for the hex-head screw and tighten it with the hex screwdriver.
4	9, 11, 20, 21	Insert a hex-head screw (20) into the back side hole of the bottom frame (11) and into the boiler (9). Tighten the hex-head screw with the dome nut (21) using the hex screwdriver and the wrench.
5	7, 9, 18	Insert a Torx screw (18) into the central hole of the cabin (7) and into the open side of the boiler (9). Tighten with the Torx screwdriver.
6	1, 3, 13	Align an axis (1) with the tapped hole of a wheel (3). Insert a Phillips screw (13) and use the Phillips screwdriver to tighten.
7	2, 5, 15	Align an axis (2) with the tapped hole of a wheel (5). Insert a Phillips screw (15) and use the Phillips screwdriver to tighten.
8	1, 4, 11, 14	Insert the free side of an axis (1) into the front side hole of the bottom frame (11). Align the axis with the tapped hole of a wheel (4). Insert a Phillips screw (14) and tighten with the Phillips screwdriver.
9	2, 6, 11, 16	Insert the free side of an axis (2) into the back side hole of the bottom frame (11). Align the axis with the tapped hole of a wheel (6). Insert a Phillips screw (16) and tighten with the Phillips screwdriver.

3.4. Execution of the experiment

Twenty operators (16 male, 4 female) among university students in the MG2040 Assembly Technology course at KTH Royal Institute of Technology are selected to participate in the experiments. The operators are equally divided in a test group (8 male, 2 female) and a control group (8 male, 2 female). Each operator in the test group watches the expert video aid and proceeds to repeat five times the assembly of the locomotive. The operator is allowed to watch either the entire video or a part of it pertaining one subassembly and proceed to the relative assembly operation(s). Conversely, each operator in the control group directly proceeds to assemble five locomotives without any specific instructions other than the assembled locomotive (see Fig. 1) and the exploded view (see Fig. 2) for reference. A researcher records the assembly time at each repetition and for each subassembly, then uses the information on the video length to remove the time for watching the expert video aid. The assembly repetitions are performed one after another without interruption.

3.5. Functional analysis of variance

The assembly time data collected in the experiments can be represented by learning curves, one for each operator. The assembly time is considered a random variable taken over a discretized interval, namely, the five assembly repetitions. As explained in the introduction of this article, functional data analysis provides tools for the statistical modelling of these curves which is necessary due to the functional correlation of the sample data collected from assembly repetitions of a same operator (the learning curve).

The experimental data produces l groups of independent random functions $m_{ij}(t)$, with $i = 1, \ldots, l$, $j = 1, \ldots, n_i$, defined over a closed bounded interval $I = [a, b]$. Let $n = n_1, \ldots, n_l$. These groups may differ in mean functions, i.e. it is possible to assume that $m_{ij}(t)$ for $j = 1, \ldots, n_i$ are stochastic processes with mean function $\mu_i(t)$, $t \in I$, for $i = 1, \ldots, l$. The null hypothesis to test is:

$$H_0 : \mu_1(t) = \cdots = \mu_l(t), \quad t \in I \tag{1}$$

The method needed for testing this hypothesis belongs to the class of a one-way analysis of variance for functional data (FANOVA). The literature has proposed many different methods to test the hypothesis in Eq. (1) and the package "fdANOVA" in R [36] allows to perform the test using 12 of these methods. Each method provides a p-value for the null hypothesis in Eq. (1). The methods are the permutation test based on basis function representation (FP test) [37], the L2-norm-based parametric bootstrap tests for homoscedastic and heteroscedastic samples (respectively, CH and CS test) [38], the L2-norm-based test with naive and bias-reduced method of estimation (respectively, L2N and L2B test) [39–41], the L2-norm-based bootstrap test (L2b test) [41] and the F-type test with naive and bias-reduced method of estimation (respectively, FN test and FB test) [42,43], the globalizing the point-wise F-test (GPF test) [44], the Fmax bootstrap test (Fmaxb test) [45] and the test based on random projections (TRP test) [46].

In this study, there are two experimental groups ($l = 2$). Each experimental group has ten participants ($j = 10$). The null hypothesis refers to the mean of the ten learning curves (i.e. the assembly times over five repetitions) of the test group ($i = 1$), receiving the expert video aid, and the control group ($i = 2$), not receiving any aid. In particular:

$$H_0 : \mu_{\text{test}}(t) = \mu_{\text{control}}(t), \quad t \in [1, 5] \cap N \tag{2}$$

One possibility to find the repetitions where the null hypothesis in Eq. (2) has to be rejected is to perform five (one for each repetition) different two-sample t-test using a Bonferroni correction for the first type error [19]. However, this approach would reduce the power of the statistical test [18].

For functional data, such as the assembly learning curves, Pini and Vantini [47] provide a method to perform point-wise and interval-wise comparisons. Their method can be used to compare the two learning curves from the experimental groups at specific time values (i.e. at each repetition). The results are five p-values for a point-wise comparison, at each time $t \in [1, 5] \cap N$, and five adjusted p-values for an interval-wise comparison, in the intervals $t \in [1, 2]$, $t \in [2, 3]$, $t \in [3, 4]$ and $t \in [4, 5]$, both indicating if the mean assembly time in the two groups differs or not.

The inferential procedure proposed by Pini and Vantini is used to select the repetitions where the null hypothesis in Eq. (2) has to be rejected. The outputs of the procedure are an unadjusted p-value and an adjusted p-value. The unadjusted p-value controls the point-wise type I error, while the adjusted p-value controls the interval-wise type I error.

4. Results

The experimental results are presented in Tables 2 and 3 , and summarized in Table 4 with means, variance and logarithm of variance at each repetition for the two experimental groups: the test group, receiving expert video aid, and the control group, not receiving any aid.

Table 2
Assembly time for the control group (no aid).

Operator j	Repetition t				
	1	2	3	4	5
1	225	170	148	149	152
2	181	192	191	121	128
3	276	199	156	155	157
4	249	159	156	136	132
5	249	177	166	139	124
6	419	260	167	112	116
7	781	334	284	217	153
8	493	415	225	242	206
9	761	273	211	187	153
10	362	166	137	113	92

Table 3
Assembly time for the test group (expert video aid).

Operator j	Repetition t				
	1	2	3	4	5
1	230	216	146	173	176
2	206	218	208	169	173
3	346	183	243	241	202
4	190	138	126	128	127
5	235	221	168	149	138
6	308	203	175	177	163
7	260	273	192	253	192
8	312	268	234	275	193
9	367	285	265	244	248
10	426	306	276	221	276

Fig. 3 shows all the learning curves $m_{ij}(t)$, with $i \in [1, 2] \cap N$ (experimental groups), $j \in [1, 10] \cap N$ (operators) and $t \in [1, 5] \cap N$ (repetitions), including their means $\mu_i(t)$ and the area A_i covered by the learning curves $m_{ij}(t)$ for each experimental group i. Fig. 4 shows and compares the mean learning curves $\mu_i(t)$ and the logarithm of the variance of the learning curves $\log(\sigma_i^2(t))$, with $i \in [1, 2] \cap N$ (experimental groups) and $t \in [1, 5] \cap N$ (repetitions). Note that, in all the figures, the values of $i \in [1, 2] \cap N$ are replaced with the labels "control" and "test". Note also that, in all the figures, all the curves are interpolated using splines in order to produce a smooth visual effect.

Although many articles (listed in Section 2) attempt to compare the mean learning curves directly from their plots, it is necessary to consider the stochastic nature of these functions in the analysis.

The 12 results of FANOVA performed with the R package to compare the mean learning curves are reported in Table 5. Many p-values are close to 0.1 and the TRP test has a very significant p-value. The GPF test and Fmaxb test also have small p-values, even though they are close to the limit 0.05. This is an indication that the null hypothesis of Eq. (2) can be rejected and the differences in the mean learning curves are to be considered statistically significant.

Table 4
Mean $\mu(t)$, variance $\sigma^2(t)$ and logarithm of the variance $\log(\sigma^2(t))$ of assembly time for each repetition t, for the test group (expert video aid) and the control group (no aid).

Repetition t	Test group (expert video aid)			Control group (no aid)		
	$\mu(t)$	$\sigma^2(t)$	$\log(\sigma^2(t))$	$\mu(t)$	$\sigma^2(t)$	$\log(\sigma^2(t))$
1	288	5291	3.72	400	42,550	4.63
2	231	2390	3.38	234	6554	3.82
3	203	2307	3.36	184	1814	3.26
4	203	2241	3.35	157	1781	3.25
5	189	1879	3.27	141	845	2.93

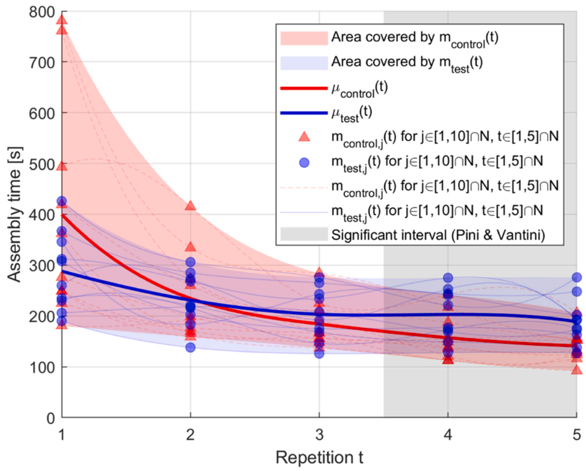

Fig. 3. Learning curves from sampled data.

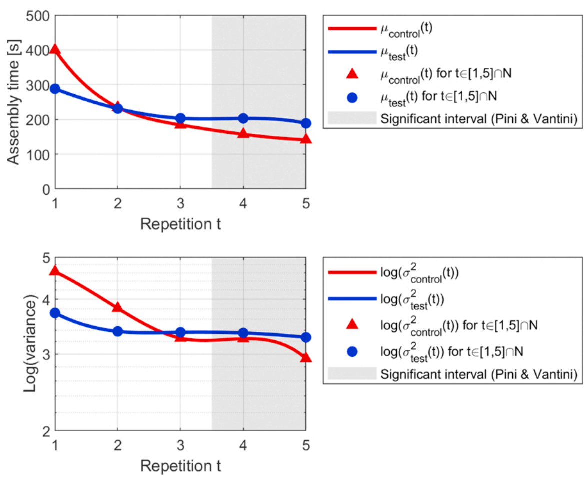

Fig. 4. Mean and log(variance) of the learning curves.

Table 5
p-Values from 12 FANOVA methods in R.

Test method	*p*-value
FP test	0.178
CH test	0.134
CS test	0.113
L2N test	0.120
L2B test	0.102
L2b test	0.121
FN test	0.133
FB test	0.148
GPF test	0.060
Fmaxb test	0.045
TRP test	0.010

The TRP test shows that the learning curves obtained from the test group (with expert video aid) and the control group are different. Thus, it is of interest to calculate at which repetitions the two learning curves differ.

The adjusted *p*-values obtained with the Pini and Vantini method are reported numerically in Table 6 and graphically in Fig. 5. The interval-wise result obtained from the adjusted *p*-values shows that there is no difference between the learning curves at repetitions $t = 1, b, 3$ (white region in Fig. 5). On the other hand, the difference between the learning curves becomes significant at repetitions $t = 4, 5$ (grey region in Fig. 5). The significant interval is also reported in Figs. 3 and 4 as a grey background region.

Table 6
p-Values and adjusted *p*-values for each assembly repetition.

Repetition *t*	*p*-value	Adjusted *p*-value
1	0.118	0.343
2	0.894	0.894
3	0.400	0.704
4	0.003	0.041
5	0.006	0.041

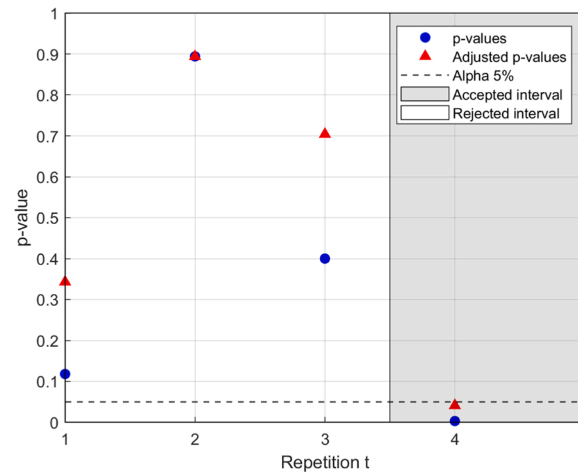

Fig. 5. *p*-Values and adjusted *p*-values (Pini & Vantini).

5. Discussions and conclusions

This article provides an overview of the works in manufacturing using the learning curve as a mathematical model and finds a methodological gap in the analysis and comparison of assembly assistance technology, whether researchers use or not the learning curves to model its influence on the operators. This article solves the gap by presenting a rigorous scientific method with the functional analysis of variance, which is better suited than the classical analysis of variance for comparing learning curves. An experimental study is performed over the implementation of a specific technology – expert video aid – with rigorous authoring methods. The results from the application of FANOVA, reported in Section 4, provide interesting insights on the influence of the expert video aid on the learning curves of the assembly operators.

From the adjusted *p*-values obtained with the Pini and Vantini [47] method, reported in Table 6 and Fig. 5, it results that there is no difference between the learning curves in the repetitions interval $t \in [1, 3]$ (Fig. 5, with white background). Thus, providing the expert video aid to the operators does not produce a statistically significant advantage. On the other hand, the difference between the learning curves becomes significant in the repetitions interval $t \in [4, 5]$ (Fig. 5, with gray background) indicating a statistically significant influence of the expert video aid in the long tail of the learning curve.

The numerical comparison of the means in Table 4 and the graphical comparison of the mean learning curves from Fig. 4 show that after three repetitions, namely, in the statistically significant interval $t \in [4, 5]$, the mean assembly time of the control group is better than the test group receiving the expert video aid.

In contrast with the statistical analysis, Fig. 4 shows that the test group receiving expert video aid performs faster assemblies in the interval $t \in [1, 3]$, thus one can say that the expert video aid generates higher learning rates for $t \in [1, 3]$, but not statistically higher. This could be explained by the large variability (see Table 4 and Fig. 4) in terms of assembly time in the first assembly repetitions, which makes it difficult to find statistically significant differences (large variation reduces the power of the statistical tests). As the number of repetitions increases, the variance decreases and the power of the statistical tests increases. The initial three repetitions of the assembly learning curves constitute what in system theory is considered a transient state.

If the statistical tests do not provide a significant answer on the effects of the expert video aid on the first repetitions of the learning curves, they surely confirm that the expert video aid is detrimental to the performance of the operators in terms of assembly time in the long run, on the tail of the learning curves. This result opens up to future studies on the causes of the *switching effect* found. This effect can potentially influence the learning curves of any technologies applied to any manufacturing systems. Limiting the comparison of two assembly aid methods to the first assembly repetition might hide the switching point and the change of the early effectiveness and the long term effectiveness of one aid with respect to the other one. The design of manufacturing aid systems can benefit from a rigorous functional statistical analysis of extended learning curves over manufacturing process repetitions.

The researchers can make one possible hypothesis on the switching effect based on the qualitative observation of the experimental assemblies: the expert video aid contains several implicit constraints on the assembly task that the operator has to learn to imitate, even against their own pre-existing knowledge or preferred – thus faster – habits. Additional implicit constraints (i.e. following the detailed procedural instructions in the video) reduce the freedom of the operator in applying their own knowledge and adapting the task to their habits or skills. This prevents the operators to further improve their performance in terms of assembly time. The effect of this adaptive component of the reduction of the assembly time appears only at a steady state of the learning curve, which is reached from the fourth assembly repetition, when the influence of the expert video aid on the reduction of the assembly time in the transient interval (first three repetitions) becomes negligible. Future studies should determine if the switching effect found in these experimental results is an isolated or a general phenomenon. Furthermore, future works can address a learning curve model that separates the transient state from the steady state in order to further identify and analyze their main components in terms of learning.

Among the limitations of this study, the following ones are worth mentioning:

- The study has been conducted in a laboratory and an industrial environment can be different from it because of increased variety, complexity and risk of the tasks;
- only one product has been used.
- the assembly operators are students with a B.Sc. degree in manufacturing that can be more educated than average industrial operators.
- the study is made with a limited number of operators (20).
- there are domains that involve mechanical-electrical-IT tasks combined in the assembly line, and the obtained results may differ in those situations.
- the steady-state often lasts for short periods of time, and the transient regime can be repeatedly initiated.
- the behavior in the transient and steady regimes might be underestimated by this work, with respect to industrial cases, due to the frequent replacement of human resources in the experiments.

Due to these limitations, this study that has to be interpreted as a trend within the indicated variables and as a valid example of how to apply FANOVA on learning curves, rather than a tool that is ready to use for designing assembly operations with video aid. Further studies are required to control the variables mentioned above and produce more general results.

Furthermore, assessing the influence of the expert aid on the assembly learning curves only in terms of video instructions constitutes an experimental design trade-off and methodological limitation of this study. It is possible and common to provide assembly instructions by means of other methods, for example with augmented reality (e.g. projecting animated assembly instructions on the assembly station). Further studies can extend and compare the obtained results with other methods.

Declaration of Competing Interest

The authors report no declarations of interest.

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