THE JOURNAL OF PROSTHETIC DENTISTRY

RESEARCH AND EDUCATION

Prediction of the learning curves of 2 dental CAD software programs

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ABSTRACT

Statement of problem. Dental clinical procedures are being replaced by digital workflows. Therefore, the time necessary to learn dental computer-aided design (CAD) software to achieve a change in the digital workflow should be evaluated.

Purpose. The purpose of this study was to predict the learning curve according to the type of dental CAD software with the Wright model and to determine the rate of improvement in the learner's working time with iterative learning.

Material and methods. A total of 40 participants with various degrees of experience with dental computer-aided design and computer-aided manufacturing (CAD-CAM) systems were recruited. The 4 specified steps of a custom abutment design were performed with 3DSystem CAD software (Daesung) and exocad DentalCAD (exocad GmbH) software and were repeated 3 times in stages. The times were analyzed with repeated-measures 1-factor and 2-factor analyses. The learning time for 300 design iterations was estimated by applying the Wright model formula, and the 300-repetition times were analyzed with the Mann-Whitney U test (α=.05).

Results. exocad had a longer mean learning time than the 3DSystem. The overall change with repeated learning was significantly different (P<.001), and all differences were found in the first to third iterations. Software-dependent differences were also observed (P=.005). The Mann-Whitney U test also revealed a significant difference between the 2 software programs (P=.015), but no significant difference was found after the 56th iteration (57th iteration: P=.051).

Conclusions. As the time reduction patterns for iterative learning differ depending on the type of CAD software, the learning curves may differ according to the type of software. As the operator's skill increased through iterative learning, the differences in learning times between the software programs gradually disappeared. (J Prosthet Dent 2019;121:95-100)

Technological improvements have been widely recognized as drivers of economic growth, and methods to predict these technological improvements are potentially very useful.[1-3] A method of predicting the cost and performance of technology was introduced by Wright[4] in 1936. In addition, the learning curve model confirmed that the production costs in aircraft manufacturing decreased with increased output.

Methods of estimating the parameters of learning curves are traditionally used for statistical analysis.[5,6] Statistical methods are appropriate when the data are sufficient, but they provide only limited results when the amount of data is small and fluctuates. Statistical methods for limited data are not straightforward, and it is costly and time-consuming to obtain complete data. Therefore, for limited data, a learning curve model beyond statistical methods should be used.[7]

Since Wright, several authors have investigated the functional relationships in learning curves.[8-12] These learning curve models include several models for measuring learning, the number of variables, and the accuracy of the learning curve.[13] Among them, the

Supported by Institute for Information & Communications Technology Promotion grant funded by the Korean government (B0101-17-1081, development of ICT-based software platform and service technologies for medical 3D printing applications) and Industrial Strategic Technology Development Program (10062635, new hybrid milling machine with a resolution of less than 10 μm development, using open CAD-CAM S/W integrated platforms for 1-day prosthetic treatment of 3D smart medical care system) funded by the Ministry of Trade, Industry & Energy (Korea).
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Clinical Implications

The repeated learning of the dental CAD software and the resulting learning curve enable the evaluation of the working efficiency and the clinical learning effect. Long-term predictive learning effects can be used to establish reasonable CAD software training in clinical practice and to increase the effectiveness of iterative learning.

Wright model was the first learning curve model and is called the log-linear model. The following mathematical expression is used in this model:

$$Y_{(X)}=Y1X^{b},$$

where $Y_{(X)}$ is the average time (or cost) required to produce in X, and $Y1$ is the time (or cost) required to produce the first unit. The expression b ($-1<b<0$) is the slope of the learning curve representing the learning rate of the learner and can be obtained by the formula

$$B=\log LR/\log 2,$$

where LR is the learning rate ($0\leq LR\leq 1$). A b value close to −1 indicates a higher learning rate and faster adaptation to task performance.[8] Although many improved learning curve models have been published, the Wright model has been used because of its more accurate results and straightforward analysis methods.[7,14-17]

The learning curve is used not only in manufacturing but also in various industrial fields.[18-20] In the medical field, all new treatment procedures require a certain time to learn, so this model has been used to evaluate treatment methods.[21-27] In dentistry, the learning curve theory was applied to the total scanning time and the change in the time necessary to perform the procedure with 2 types of digital oral scanners.[28,29] In assessments of dental education, the clinical skills of dental students were compared by using learning curves, and the relationship between formal education and repeated learning was examined.[30] Prior studies have shown that computer-aided design (CAD) learning is closely related to the learning curve.[14,31] However, the authors are unaware of an experiment in dentistry to predict working time by applying the learning curve model.

The purpose of this study was to predict the Wright learning curve model for dental CAD software by applying the learning curve model, and to study the tendency of improvement in the learner's working time with iterative learning. The null hypothesis was that no difference would be found between the predicted curves of the 2 types of CAD software when learners iteratively learned to customize an abutment.

MATERIAL AND METHODS

For each CAD software, a sample size of 40 was calculated by using power analysis software (G*Power v3.1.9.2; Heinrich-Heine-Universität Düsseldorf) (actual power=80.7%; power=80%; α=.05). A total of 40 participants showing varying levels of experience with dental computer-aided design and computer-aided manufacturing (CAD-CAM) were recruited to evaluate the learning curve of dental CAD software. The participants included 20 experienced dental technicians, 10 dentists in Kyungpook National University Dental Hospital, and 10 dental graduate students.

A scan file for a custom abutment design was prepared by scanning a gypsum cast with an implant placed on the left maxillary first molar; the scanning was performed with a desktop scanner (FREEDOM HD; DOF). The abutment design was prepared by storing the scan files in each CAD software program, which were installed on 2 computers with identical specifications.

Two types of CAD software were used: 3DSystem CAD software (Daesung) and exocad DentalCAD software (exocad GmbH) (Fig. 1). The 3DSystem CAD software offers custom abutment design capabilities for fixed prostheses and implants. According to the manufacturer, it is currently only available in Korea but will be released internationally in the future. A custom abutment form was defined based on the design factors that could be set in each software program (Table 1). Each learner was given an hour of theoretical education and watched a rehearsal video of a custom abutment design. Then, before evaluation, each participant performed 1 computer exercise with each CAD software program. Because the order of learning a particular software can affect the learning curve, in this study, 20 of the 40 learners learned exocad dentalCAD first and the other 20 learned the 3DSystem CAD software first, thus reducing this effect.

In both CAD software programs, the learner performed custom abutment designs in 4 steps: first, running the programs and entering basic information; second, loading the files; third, setting the predesignation conditions of the abutment; and fourth, designing the abutment (Fig. 1). Participants ran the software on the computers and then wrote the name of the participant where the patient's name is written. They then assigned the implant to the maxillary left first molar location and set it to the custom abutment design. They designed the custom abutment by loading the scan files of the maxillary and mandibular models and setting them according to the preset design conditions (Table 1). The recorder measured the time taken by each learner to perform each step and the time it took to generate the final design 3 times. Assessments with both types of software were performed on computers with the same specifications to avoid differences in working time depending on the

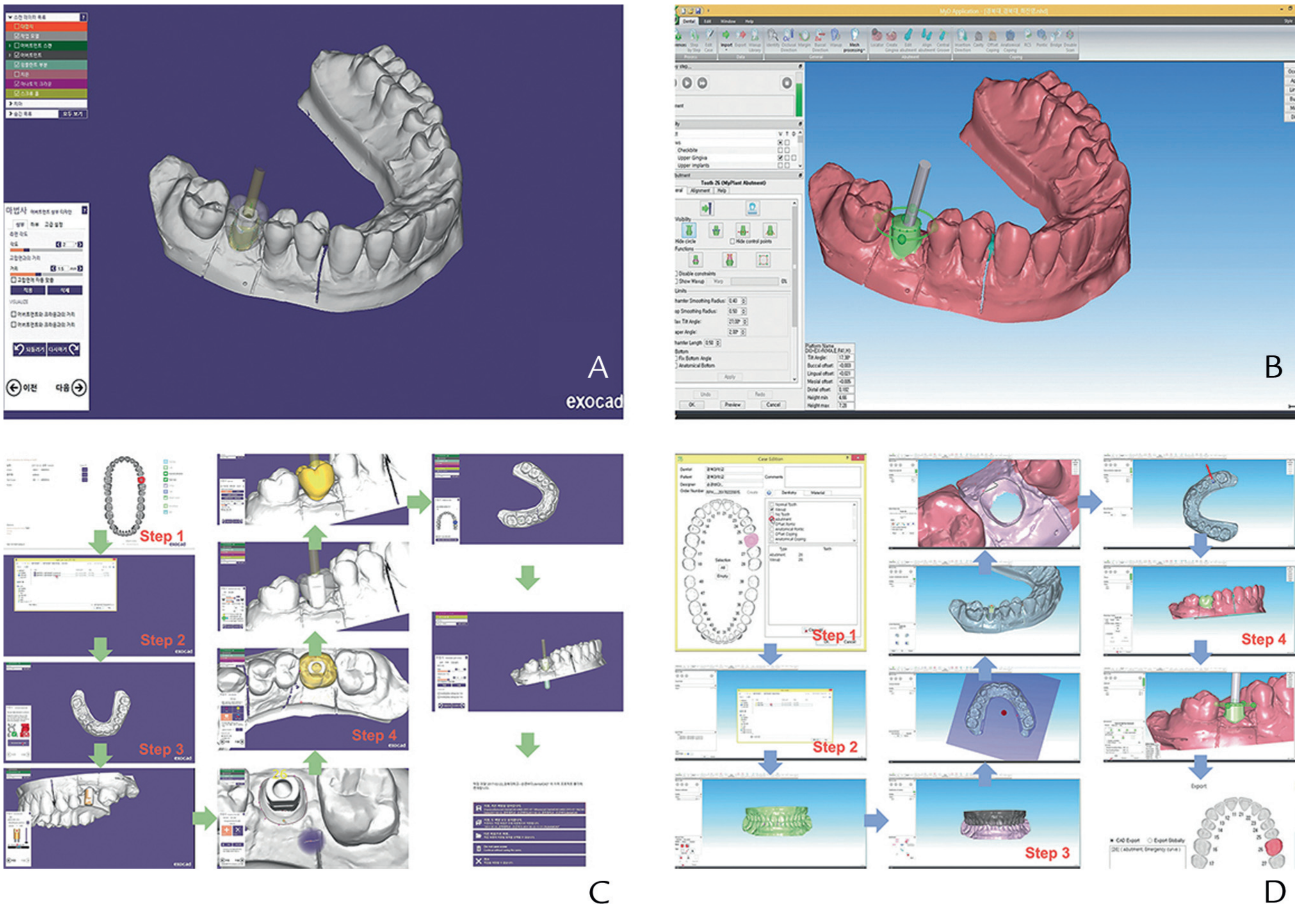

Figure 1. Custom abutment design procedure in computer-aided design software program. A,C, exocad. B,D, 3DSystem.

Table 1. Design conditions of custom abutment

Condition	exocad	3DSystem
Abutment angle	4 degrees	2 degrees
Margin Line	Equigingival margin	

performance of the computer. At this time, when the design passing standard was not satisfied, the additional design time was also measured.

To understand the learning effect of each CAD software program, iterative learning was conducted, and the learning curve was based on the time of the final design. Based on the recorded time, the learning rate of the 40 participants was calculated by dividing the previous learning time by the next time corresponding to each CAD software program. The Wright model formula was then applied to estimate the learner's 300-repetition learning time.

First, the normal distribution of data was investigated with the Shapiro-Wilk test. Because the 3-time iterative learning time was normally distributed, repeated-measures 1-factor analysis was used to determine whether the time reduction was significant, and repeated-measures 2-factor analysis was used to identify the difference in software programs. The differences between each repetition of learning were examined by using the Tukey HSD test. The 300-time estimated time did not have a normal distribution, and the Mann-Whitney U test was used to determine the differences among software. Statistical analysis was performed with statistical software (IBM SPSS Statistics, v23.0; IBM Corp) (α=.05).

RESULTS

Among the participant groups, the dental technicians showed the lowest working time for all 3 repeated measurements, then the dentists and dental students (Table 2). In the 3 repeated measurements obtained from the 40 participants, the time reduction as a result of repeated learning for each software program was significant (P<.001). A difference was found in the overall time variation with iterative learning (P<.001), and the data showed additional differences in repetitive learning among the first, second, and third repetitions. The data also showed differences among software programs (P=.005). No interaction was found between the time and the software program (P=.830) (Table 3, Fig. 2).

Table 2. Comparison of mean working time (seconds) in first, second, and third repetitions among participant groups

Trial No.	Dentist (n=10)	Dental Technician (n=20)	Student (n=10)
1	178.7 ±50	149.1 ±52.8	199.5 ±36.4
2	140.5 ±29.7	129.5 ±42.9	146.3 ±35.6
3	126.1 ±28.3	110.3 ±29.1	131.4 ±27.7

Table 3. Comparison of mean working time (seconds) in first, second, and third repetitions by software (n=40)

	CAD Software (Mean ±SD)	
	exocad	3DSystem
Trial No.		
1	181.5 ±55.6[a]	156.7 ±46.6[a]
2	146.7 ±41.0[b]	126.2 ±33.1[b]
3	129.4 ±24.8[b]	107.1 ±28.8[b]
P		
Time	<.001*	<.001*
Time	<.001**	
Group	.005**	
Time×group	.830**	

SD, standard deviation. Different superscript letters indicate significant differences, *P*<.05. *Significance determined by repeated-measures 1-factor, *P*<.05. **Significance determined by repeated measures 2-factor analysis, *P*<.05.

The estimated learning curve over 300 iterations of each software program is shown in Figure 3; a graph of the averages is shown in Figure 4. Exocad dentalCAD had a higher learning time than 3DSystem (Table 4, Fig. 4). As revealed by the Mann-Whitney U test, there was a significant difference between the 2 software programs (*P*=.015), but there was no significant difference after the 56th iteration (57th iteration: *P*=.051) (Table 4).

DISCUSSION

The purpose of this study was to predict the learning curves for the 2 CAD software programs with the Wright model and to determine how the learners' performance improved with iterative learning. To do this, learners repeated the custom abutment in 2 types of CAD software. The null hypothesis was that no difference would be found in the 300-repetition prediction curves. The results of this study show that the null hypothesis was rejected from the second repetition (*P*=.015) but that the 57th iteration was accepted as critical (*P*=.051) (Table 4).

In this study, CAD software learning tasks were repeated 3 times by the learner, and as the number of repetitions increased, the skill increased and the time necessary to complete the task decreased (*P*<.001) (Table 3, Fig. 2). This resulted in increased proficiency through iterative learning and the learning effect, which decreased the time required to perform the procedure. However, in the medical field, improving the learning curve through clinical experience to increase the proficiency of special surgical procedures is difficult, and

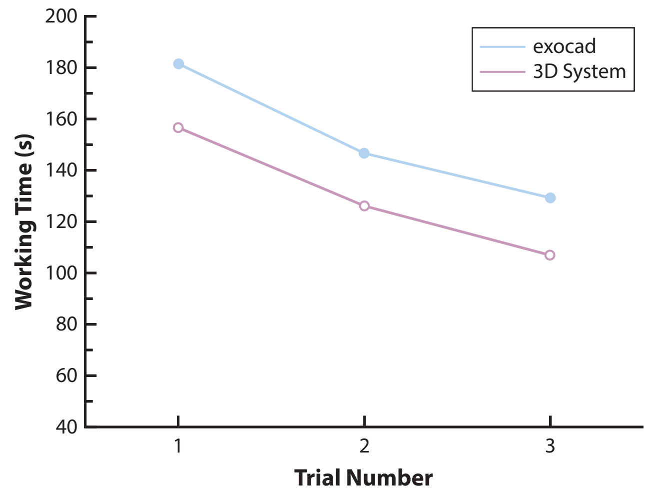

Figure 2. Learning curve including mean time of first, second, and third repetitions of abutment design.

clinical trials should be used.[25] For this reason, first-time users should study the procedure repeatedly during the clinical trial to improve the learning curve.[26]

Published studies on learning dental CAD software are lacking. However, Kim et al[28] and Lim et al[29] described the learning curve for the time required to scan the complete mouth with an intraoral scanner. They studied 2 commonly used intraoral scanners in clinical practice and found that repeated learning is necessary for effective clinical application. In this study, the findings for the dental CAD software, like the intraoral scanner, confirmed the learning effect through iterative learning and confirmed the difference in learning speed among CAD software programs (Table 3). Two widely used CAD software programs were not compared. The study compared the learning curve of the 3DSystem CAD software (not widely known outside Korea) with the globally popular exocad software.

A total of 40 participants were recruited according to their experience with dental CAD-CAM software in order to obtain the learning times of first-time users and experienced operators. In other studies, the learning curve of a new surgical procedure was compared between novice and experienced users. The success rate of the experienced group was significantly higher.[27] Because the learning curves obtained from experienced and nonexperienced individuals are different, the learning curves of each dental CAD software must show different learning rates in different groups in order to be representative. Therefore, in this study, experienced dental technicians and nonexperienced dentists in Kyungpook National University dental hospital and dental school graduate students were recruited. Then, the learning curves for each CAD software program were evaluated among these participant groups.

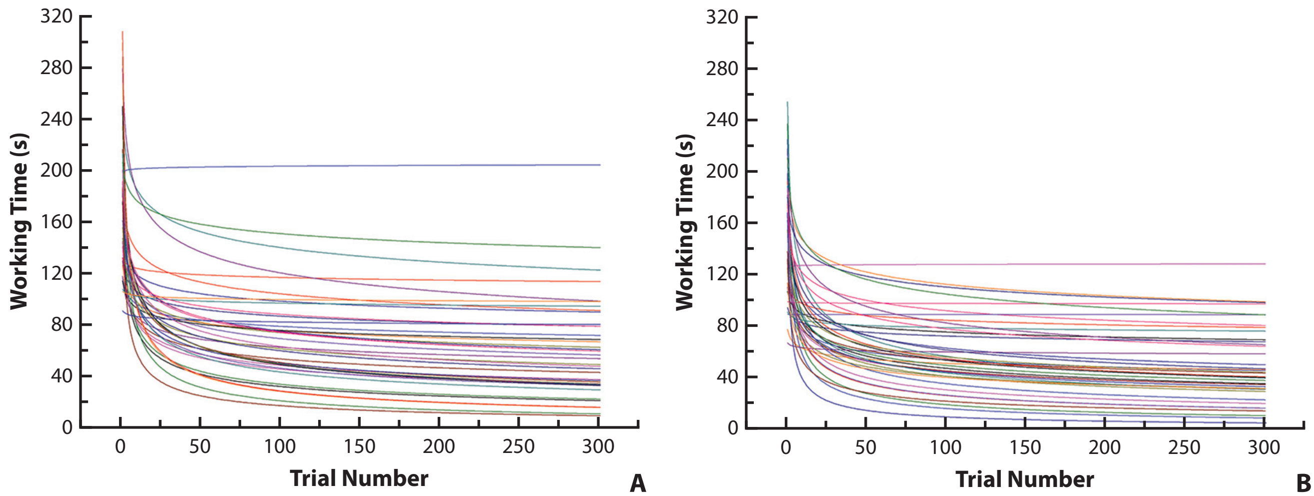

Figure 3. Learning curve of working time by using learning curve model. A, exocad. B, 3DSystem.

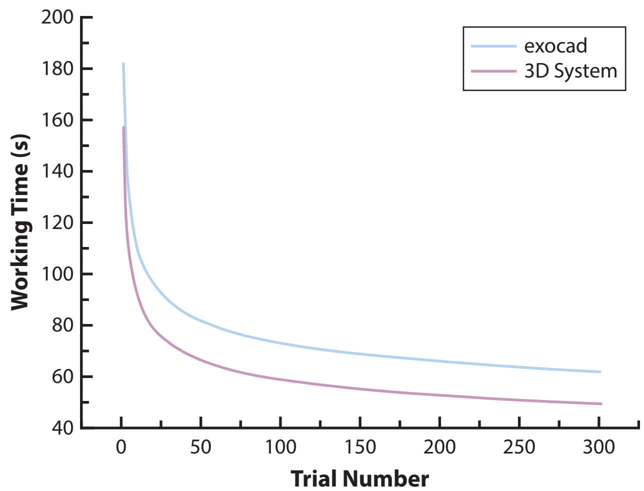

Figure 4. Learning curve of mean working time by using learning curve model.

Table 4. Comparison of mean working time (seconds) by using learning curve model (n=40)

Trial No.	CAD Software Mean ±SD exocad	CAD Software Mean ±SD 3DSystem	*P*
1	181.5 ±55.6	156.7 ±46.6	.078
2	153.8 ±37.8	131.4 ±33.0	.015
3	140.3 ±32.5	119.1 ±28.7	.005
4	131.8 ±30.5	111.3 ±26.9	.003
5	125.6 ±29.8	105.8 ±26.0	.002
55	80.1 ±35.8	65.0 ±27.5	.050
56	79.9 ±35.9	64.8 ±27.5	.050
57	79.7 ±35.9	64.6 ±27.6	.051
58	79.4 ±36.0	64.4 ±27.6	.054
59	79.2 ±36.0	64.2 ±27.6	.057
298	61.8 ±39.1	49.0 ±29.1	.128
299	61.8 ±39.1	49.0 ±29.1	.128
300	61.8 ±39.1	49.0 ±29.1	.128

SD, standard deviation. Significance determined by Mann-Whitney U test, $P<.05$.

The results show that the final completion time of the design differed depending on the type of CAD software. This is because the design process is different in each software program. However, these differences were not a problem because the effect of iterative learning was investigated by using software. To reduce the learner's time difference, the time was measured under the specified design conditions (Table 1).

In this study, the results of the Wright model show that the work time does not converge to 0 in the 300th estimate because x has an exponent and the exponent has a value between 1 and 0. Therefore, although the work time decreases toward 0, the degree of reduction is very small.

In this study, a learning curve model with more accurate results was applied, and the method of calculating long-term iterative learning and improving the learner's performance at a lower cost and in a shorter time without actually experimenting was studied. With easier and less time-consuming investment, these results are excellent for the evaluation of long-term clinical skills in the dental field.

This study could not consider various influences such as the lack of understanding due to less iterative learning or forgetting the design process. The participants completed all the assessments in a day, and the experiment proceeded without considering the effects of long-term memory. In addition, some participants had low learning ability through education, and some who were not skilled in computer operation did not show decreased learning times. These factors must be considered for the learning curve to be representative. Further studies involving a number of iterative learning tasks are needed to estimate the learning curve and to determine the difference between the learning curve and actual measurement values.

CONCLUSIONS

Based on the findings of this study, the following conclusions were drawn:

1. The 2 types of CAD software assessed showed different time reduction patterns for iterative learning and different learning curves.
2. These learning curves showed that the 3DSystem, which takes less time at the beginning of use, is more advantageous.
3. The difference in learning time between the 2 kinds of software gradually disappeared with iterative learning and would be expected to show the same working time in long-term experiments.

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Acknowledgments
The authors thank the participants in the Department of Prosthodontics, School of Dentistry, Kyungpook National University, for their time and contributions to the study.

https://doi.org/10.1016/j.prosdent.2018.01.004