LEARNING COMPLEX MOTOR PROCEDURES

Can learning a complex motor procedure be predicted by other motor procedures?

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Abstract

In contrast to open surgery, from the late 1980s another form of surgery is taking over in this field, which is called Minimally Invasive Surgery (MIS). This MIS does come with a lot of advantages. Especially the patients benefit from a faster recovery and less (visible) scars after surgery. However, MIS comes with its disadvantages as well. It is harder to learn this specific skill and more mental effort is asked from the surgeons. Because not every trainee seems to reach the same level of proficiency on MIS and is able to learn this in the same amount of time, it is needed to find a way to predict this. Therefore, in this research, it will be examined whether dexterity tasks can predict the learning of another dexterity task. If this would be possible, this perhaps also works in the field of MIS.

In this research four tasks are performed by every participant (N=40). A Buzz wire task, folding origami, performing a knot and a drawing task are done. The tasks are each done 20 times, while time is tracked by the researcher. From this data learning curves are derived for each sequence (per participant, per task) and analysed. Three parameters are captured from the learning curve: previous experience, learning rate and maximum performance.

The results showed only a high correlation between Drawing and Origami on the maximum performance. The other correlations were not found relevant. First, this suggests that perhaps only predictions are possible on the maximum performance and not on the learning rate. Second, these dexterity tasks are possibly based on different skills. Where the Drawing and Origami can be based on the same skill, the other two tasks are not. Therefore, further research should be done on prediction the specific skill that MIS is based on. This should focus on the maximum performance people will reach on these tasks. When this holistic approach does not seem to be working another possibility is to focus on the use of Virtual Reality to make predictions in MIS.

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Introduction

Starting in the late 1980s, a change in the medical world was the use of minimally invasive surgical (MIS) procedures. This was a big turn in the way surgery was being practiced. Which is striking for the field of surgery that has always leaned on strict traditions and usually only goes with gradual changes (Gallagher & Smith, 2003). This new way of doing surgery came in quick and was quite unexpected. One of the reasons for MIS becoming more and more popular is that it has, if being practiced in the good way, many benefits. This induces that MIS is now an important subject in the medical world. Although it has been there for a while, still not everything is known about it. Therefore, more research on MIS is still needed.

This impulse in the field of surgery came with some difficulties as well. Research has discovered that using MIS can lead to more medical failures. Particularly, this occurs the first times the surgeon uses this kind of surgery, because it is quite hard to learn this specific skill. This can lead to some specific implications, that are not or less found with open surgery (Gallagher & Smith, 2003). One example of these specific complications is the bile duct injury. During laparoscopic cholecystectomy (surgical removal of the gall bladder), the exact surgical area can be unclear. In some cases, wrong decisions are made by the surgeon leading to damage in the wrong area. Because the work of the surgeons is affecting the wellbeing of humans thoroughly, it is very important to minimize the risks in this kind of surgery. Therefore, it needs to be clear which persons are able to become a good surgeon after training, and at which point someone has reached a proficient level of performance where risks are reduced enough.

Besides medical failures are not preferred by surgeons and their patients, it can affect the hospital were this happened as well. It can lead to a bad reputation, because there is an increased public awareness on medical errors (Oyebode, 2013). Nowadays it is quite common to read all about the performance in a particular hospital before undergoing a surgery. All information about medical risks and failures in a particular hospital can be found on the Internet. This is one additional reason why MIS needs to be examined. To reduce these errors in hospitals, it is needed to take into account the human fallibility of the surgeon (Kalra, 2004).

What became clear is that one factor is the lack of experience of the surgeon. The first few surgeries the surgeon does, have higher risks on implications. This implies that it is preferable that the surgeon did have a lot of practice before starting with these kinds of surgeries. However, not enough is known about the process of learning this skill. The usual training of a surgery in the operating room used for open surgery is not adequate, because learning MIS is more complex and more time consuming (Silvennoinen, Mecklin, Saariluoma, & Antikainen, 2009). What is known, are the difficulties the surgeon has performing MIS, in comparison to a normal surgery. Most of the difficulties had to do with cognitive, ergonomic and psychomotor aspects (Gallagher & Smith, 2003). One part of improving MIS is reconsidering all the instruments that are used during the surgery. Moreover, when integrating MIS in daily practice, human factors of the surgeon must be inspected.

Multiple human factors aspects need to be considered in MIS. During MIS other instruments are used than in open surgery and the surgical area is shown on a monitor. When handling the instruments, the body wall causes an effect were the movements are counterintuitive. This is called the Fulcrum effect. The movements are reversed to what is shown on the monitor, this makes it harder to see what the surgeon is doing exactly. Next to this effect other factors make MIS a cognitive highly demanding task. The surgeons need to solve complex problems and make quick decisions, both ask a lot of attention from the surgeon (Silvennoinen et al., 2009).

In previous research, cognitive and ergonomic factors were used to predict MIS. If these factors are usable for making predictions in MIS, this can be seen as the most desirable way of prediction. It takes less time and costs less money. However, until now, this has not yet resulted into a possibility of prediction. A new way of doing research on learning this complex motor procedure would be taking a holistic view. Not only should the separate parts of this skill be examined, such as psychomotor skills and visual ability. The skill should be seen as a whole, where the learning on this procedure can be compared to learning other complex motor procedures. Then it would become clear if an overall factor exists on learning complex motor procedures. If that would be the case, it can be tried to predict one's learning curve on MIS instead of looking at the separate factors. This can be seen as the second most desirable way of making predictions. It takes more time and costs more money, but this is still doable. If the two options mentioned before both do not seem to be useful for this predictions, the last, least desirable, option of making these predictions would be that this is only possible by using MIS itself. This approach will certainly work, but is not very efficient.

For now, the focus lays on the holistic approach. To find out if such an overall predicting factor exists, research needs to be conducted on how people learn such tasks. Then it can be examined if correlations can be found between the learning of these tasks. In other words, it will be examined if it is feasible to predict tasks with other tasks. If this would give positive results, the same would possibly work on predicting the learning of MIS.

It should be determined what complex motor procedures exactly will be used in this research. Most preferred are procedures that are in some way equivalent to the practice of MIS, for example tasks that make use of the same kind of dexterity skills and are cognitively demanding. Also, it is desired that the skills are not common used every day. Because then these will be new tasks for the participants, which one will learn according to the learning curve. While exploring the possibility of prediction between tasks, it comes in handy that they are in some way similar to MIS. In this way they are probably learned in the same manner as MIS. Then the outcomes tell more about the possibility of prediction on MIS, because less other factors are taken into account.

In this research the participants will perform several of these dexterity tasks. By letting them do these tasks multiple times, it is possible to examine their learning curve. This will give an insight in how the participants will learn the different tasks. When comparing these learning curves, it will become clear if their performance would be more or less the same on the different tasks. This could be a sign common factors are present, which determine how one learns a complex motor skill. This could mean that prediction could also be possible on other complex motor procedures, such as MIS.

The research will be conducted to examine to following research question; Can the way people learn a complex motor procedure be predicted by learning another complex motor procedure? Where an association in the learning processes between different tasks is expected, that is related to training needed and the maximum level of proficiency one can reach.

Minimally invasive surgery

Minimally invasive surgery is called so because of the way it is practiced. The surgery is performed in such a way that is less invasive than open surgery. In contrary to open surgery only small wounds are made, therefore less recovery is needed (Wickham, 1987). The surgeons use endoscopes to look inside the body. The handling of the instruments happens from outside the human body, accordingly there is no direct contact with the diseased tissue and no direct vision on this area (Cao, MacKenzie, & Payandeh, 1996). It is not needed to make a large incision and show all of the surgical area. At present, the techniques in every field of surgery have been revised for MIS, where conventional approaches were adjusted (Fuchs, 2002). One of the drawbacks of this new direction of MIS is a prolonged learning curves for the surgeons.

Multiple factors that are responsible for these difficulties are described by Gallagher and Smith (2003). One of these is about perceptual conversion. The surgical area is shown on a monitor. Therefore, it is shown in 2D instead of 3D and only from one point of view. Due to the fact that it is only viewed by one camera it is harder to see depth. Also, the scaling on the screen provides a problem. Another problem on the spatial aspect is that the surgeon cannot control the camera's orientation directly. All of these spatial complications together make it harder for the surgeon to see exactly what he or she is working on. Which can lead to disorientation and misinterpretations.

Further, ergonomic difficulties are reason for some of the mistakes that are made during MIS. Partly this is caused by the fact that the surgeon has to deal with indirect manipulation of the instruments. With the instrument manipulation in MIS it is only possible to move in five degrees of freedom, compared to 7 degrees in open surgery movements (Gallagher & Smith, 2003). The instruments being used have a great impact on the time needed for the surgery, for example the Fulcrum effect and less degrees of freedom both extend this time (Hodgson, Person, Salcudean, & Nagy, 1999).

One important aspect that leads to higher risks on the surgery is the degree in which the surgeon is used to the materials and to the new way of doing surgery. MIS operations are demanding and have to do with tasks that are spatial and perceptually difficult (Silvennoinen et al., 2009). Therefore, special attention must be given to these skills in training. When hospitals started to use MIS, not enough attention was paid on the time needed to learn this skill. This has led to surgeons that were not prepared enough to do this kind of surgeries.

The learning curve

Before a surgeon is ready to perform MIS, the surgeon has to undergo a whole process of learning. The complexity of the operation and equipment requires an optimal training program. Special attention must be given to the learning stages of the trainees. Also, the training must consist of clear goals, trainees must be motivated an receiving sufficient feedback to create an optimal training program (Dankelman, Chmarra, Verdaasdonk, Stassen, & Grimbergen, 2005). When examining the learning of a complex skill, one can use a learning curve. A learning curve is a mathematical representation between the learning effort and the learning outcomes and can easily be visualized. One form of a learning curve is based on the exponential law, which is according to Heathcote, Brown, & Mewhort (2000) the most parsimonious to use as a law of practice. An example of this learning curve can be seen in figure 1.

A learning curve is not linear, but the slope of the curve changes over time. The effort needed for the task is reduced each trial, but the reductions diminishes over time (Hinze, Asce, Olbina, & Asce, 2009). In other words, the learning at the first trials goes fast and decrease over time. Several important aspects characterize the learning curve. First, it has the initial performance level; this is previous experience one has on the subject. This is the level someone has already reached before the learning is observed. In figure 1 no initial performance is shown. Second, the slope of learning; this tells something about the speed of learning. The learning rate changes over time. Third, the upper asymptote can be seen in the graph. This is the maximal performance on the task. One is not very likely the reach this performance, but while practicing the learner will come closer and closer to this level.

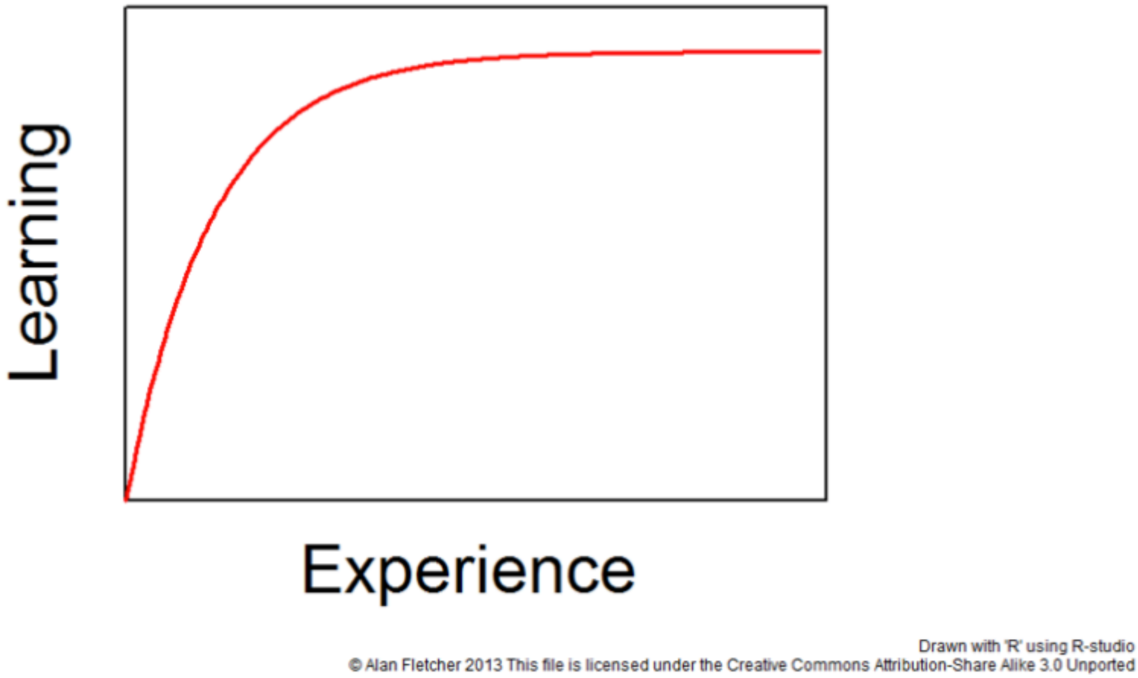

Figure 1. *Representation of a learning Curve*

According to research on learning curves by skill acquisition (Grantcharov & Funch-Jensen, 2009) most people will acquire the skills needed for MIS with enough training. In this research four different learning curves were found. Of which one was derived from a group of participants that underperformed and did, unlike the other groups, not improve on this particular skill. This could mean some people have much more difficulties learning laparoscopy. It seems necessary to identify those persons, if they will never reach proficiency in this field.

Previous research

To identify the persons that possibly would not be able to perform the skills of MIS, previous research has been done. In other fields than MIS, the use of validated psychometric tests has been found useful in making predictions. Therefore, lot of research has been done on MIS to find a predictive factor of these psychometric tests as well. Until now without clear successes (Gallagher & Smith, 2003). However, some associations are seen, nothing really evident has been found in this topic. For example research of (Buckley et al., 2014) did find a small predicting factor in aptitude. Aptitude was measured in several aspects, such as visual-spatial ability, psychomotor skills and depth perception. In this research, despite great disparity in learning curves, participants with higher fundamental abilities were more likely to perform well on these tasks. In research of Wanzel et al. (2003) it was also found that visual-spatial ability was associated with skilled performance, however it was not usable for selection on this skill. Other research (Luursema, Buzink, Verwey, & Jakimowicz, 2010; Hedman et al., 2006) did found some associations with visual-spatial ability, but only on early learning. No relations were found on the further stages of the learning process. According to Stefanidis et al. (2006) psychomotor skills are limited in predicting laparoscopic performance. Others (Hamstra, 2006; Ritter, McClusky, Gallagher, Enochsson, & Smith, 2006) have found as well that these predictions cannot be made, only some predictive value was found on the beginning of learning with novices.

Also a lot of research is done on cognitive abilities, these seem to be closely related to performing MIS. However, these cognitive abilities cannot always be used as a predicting factor. In research on cognitive abilities (Groenier, Schraagen, Miedema, & Broeders, 2014) no relationship was found on the performance of MIS and the steepness of the learning curve on this skill. Or in other words it was not found that people who scored higher on the cognitive tests learned MIS quicker than other participants. Another article (Bann & Darzi, 2005) states that no associations are found with cognitive tests, manual dexterity, visual spatial ability and personality testing.

Previous research has found multiple aspects that are somehow associated with learning MIS. However, not yet has this been very successful in predicting the performance of the surgeon on this particular skill. Because of the fact that not everyone seems to be able to learn this skill it may be necessary to look further for a predicting factor on learning MIS. Since this has not been found in the several components related to MIS, this research takes a holistic approach. Where instead of looking at the components of a skill, we compare the whole skill with another skill. Therefore, similar skills will be examined whether they are related in learning these kind of skills. If such a predictive factor will be found, this perhaps could also be the case in MIS and could be used to select people in this field.

Pilot data

To test the proposed research, first a pilot test has been done where five dexterity tasks were suggested. All tasks were in some way related to MIS, since they had to do with motor skills, were cognitive demanding and had to do with the spatial orientation. The five tasks were tested on four participants. The pilot was done to check whether these tasks would be suitable for the eventual research. A short description of the tasks will follow.

The Duncan Loop – the participant was given a rope and was instructed to perform a knot.
Origami – the participant received instructions and to fold a fox from the given paper.
Buzz wire – the participant had to follow a wire with a loop, while trying not to touch it.
Mirror drawing – the participant had to draw a figure, but could only see this through a mirror.
Rubber band trick – the participant had to perform a figure with the rubber band.

The five proposed tasks were each performed by three or four participants. They did each task 20 times while for each trial the time was measured. Also errors and/or performance were taken into account. This data had been analysed with R. While discussing the pilot data most attention was given to the computed learning curve per task. On the rubber band trick this learning curve was not very evident. On the other four tasks it was clearly visible. Besides, during the pilot, it was noticed by the researchers that the rubber band trick was not very convenient for this research. It was hard to learn this trick and the instructions were not very clear. Because of these two reasons it was decided to leave this task out and perform the research with the other four tasks; the Duncan loop, Origami, the Buzz wire and the Mirror drawing. There was also a slight moderation on the Duncan loop, where it was decided to do only 10 trials instead of 20, because it was noticed that the maximum performance was reached by this time.

Methods

Participants

This research was conducted with 40 participants, 8 were male and 32 were female, 26 of the participants were Dutch and 14 were German. They were aged between 18 and 76, M= 28.05, SD = 14.01. In this group 36 persons were right handed, 3 were left handed, and one person was mixed handed. The participants were found by convenience sampling. They all signed an informed consent form.

Apparatus

For each task specific material was used. For the Duncan loop a plain rope was used, with a length of approximately 1 meter. For the Origami task plain white paper was used, cut into squares. For the Buzz wire, a handmade Buzz wire was used. It had a LED, which would light up if an error was made. This LED had a small delay, so not every tick was counted. And for the Mirror drawing a cardboard box was used were on both sides openings were cut out. A plain mirror was used and paper with a printed figure. The instructions the participants received can be found in Appendix 3.

Procedure

In this research a within-subjects design was used. All participants had to do the four tasks, the order of this tasks changed per participant. The participants were informed before starting the research that they had to do four tasks and the number of trials. First, a few questions were asked about demographic data (age, nationality, etc.) and experience on working with your hands, for the question list see Appendix 1. Then the participants did get instructions for the first task. After all trials were finished, the participants were asked to estimate their perceived initial and end performance. After a 5-minute break, the next task was started.

The four tasks were based on the tasks in the pilot study. The Rubber band task was left out. The participants had to do the Duncan loop, Origami, the Buzz wire and the Mirror drawing. Different from the pilot study was the fact that the Duncan loop had to be done only 10 times instead of 20 times, because in the pilot study was found that the maximum performance was reached by this point. For every trial the time was tracked by the researchers and noted down on the observation form. On this form other observations done during the researcher could be noted down. For this observations some coding was done on beforehand, for example, note down that the participant was motivated (M), Frustrated (F) or the participant took a lot of time reading the instructions (I). Besides, the performance of the participant could be included on the form and other additional observations from the researcher. The observation form can be found in Appendix 2. Furthermore, the researcher did tell after every 10th and 17th trial how trials were left.

Data analysis

For every task the times tracked each trial were analysed. Some cleaning was done on this data, were obvious mistakes were deleted. The data that was used was derived from non-linear mixed-effects modelling, based on the formula from Heathcote et al. (2000). In this formula is some ambiguity with the amplitude parameter. Therefore, an adjustment was done in the parametrization. The amplitude is moved to the exponent and now models the virtual previous experience, leading to the following formula:

$$Y_{PtN} = Asym_{pt}\,(1 + e^{-Rate_{pt}(N+Prev_{pt})})$$

In this formula: ***p*** *= participant;* ***t****= task,*

Asym*= is the asymptote of maximum performance, which is reached asymptotically with continued practice.*

Rate*= the overall speed of learning.*

This resulted in an estimated learning curve per sequence, so to say a learning curve per person, per task (40x4 learning curves). Three parameters were derived from this data: the previous experience, the learning rate and the maximum performance on the tasks. The analysis was done in R.

Results

This research was based on the three parameters of a learning curve; Parameter A – the maximum performance. An estimation of the upper asymptote is given for the maximum performance on the task. Parameter B - Previous training. This is the performance level at the beginning. Most participants did not have real training on these particular tasks, but all differed in initial performance. And parameter C – the learning rate. Here the slope of the learning curve is used.

For the three parameters the scores are represented for each tasks below. There are some differences on the scores per parameter. In table 1 and figure 2 the scores are given for previous experience. On this parameter the scores on each task differ, but they are quite close to each other. There is also a slight difference in how spread out the scores are. For example, on Drawing the scores are more spread out than on the other tasks, see figure 2.

Table 1

Descriptive Statistics Previous Experience

	Mean	SD	Minimum	Maximum
Buzz wire	0,52	2,56	-7,10	3,42
Drawing	-1,38	2,91	-7,99	3,75
Duncan Loop	2,21	2,23	-5,12	5,05
Origami	-1,34	2,62	-8,65	2,25

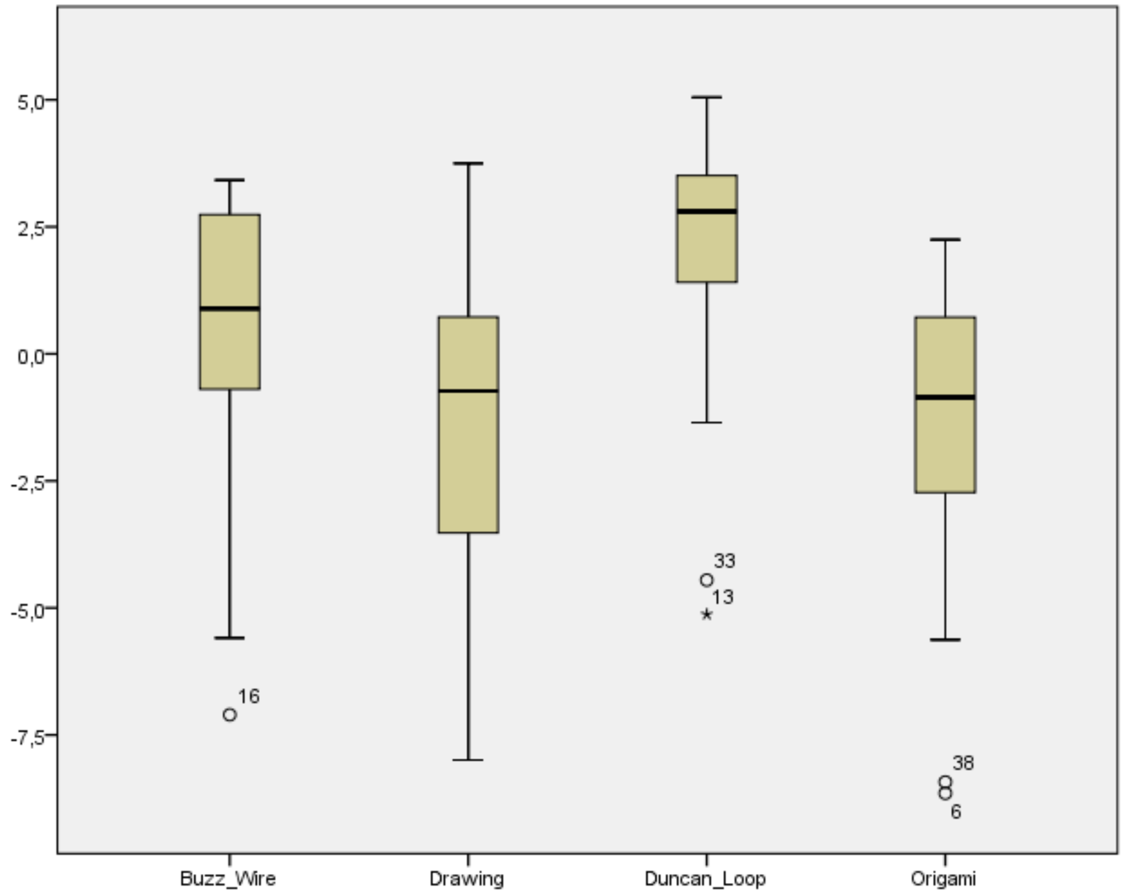

Figure 2. *Boxplots on the Previous Training on the Tasks,*

In table 2 and figure 3, the scores on the slope are shown. The mean scores are very close to each other on the different tasks. Most striking is the stretch on the Duncan loop which is much larger than the other tasks, see figure 3.

Table 2

Descriptive statistics Learning Rate

	Mean	SD	Minimum	Maximum
Buzz wire	-.15	.07	-.32	.04
Drawing	-.05	.11	-.19	.33
Duncan Loop	.19	.24	-.13	.84
Origami	-.01	.13	-.24	.32

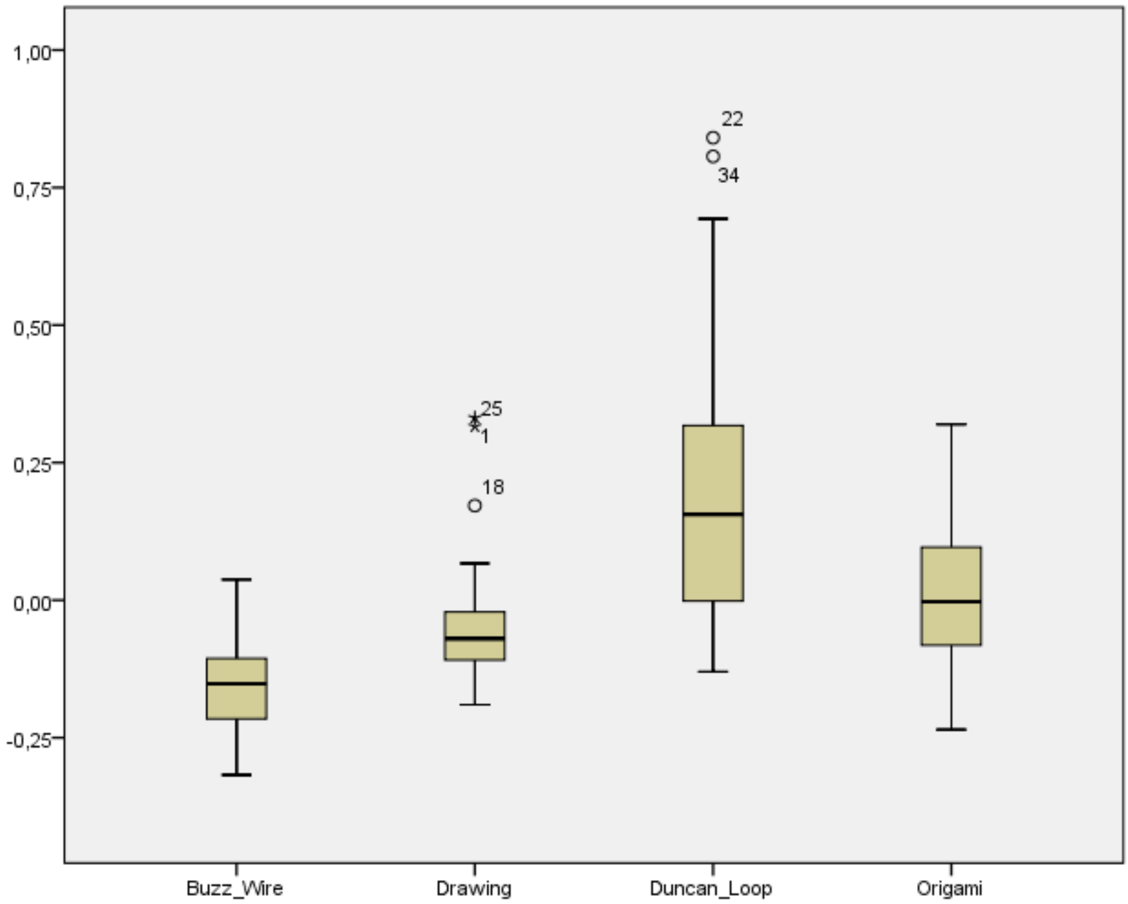

Figure 3. *Boxplots on the Learning Rate on the tasks.*

The third parameter of the learning curve is shown in table 3 and figure 4. The table demonstrates that the scores differ remarkably. The differences are much larger than on the other parameters. One further striking detail is the stretch on the score of the Duncan loop, which is much larger than on the other tasks.

Table 3

Descriptive Statistics Maximum Performance

	Mean	SD	Minimum	Maximum
Buzz wire	3,84	11,01	-9,61	48,50
Drawing	7,75	18,85	-11,43	82,34
Duncan Loop	-13,30	6,85	-18,95	19,26
Origami	2,21	11,52	-11,26	53,46

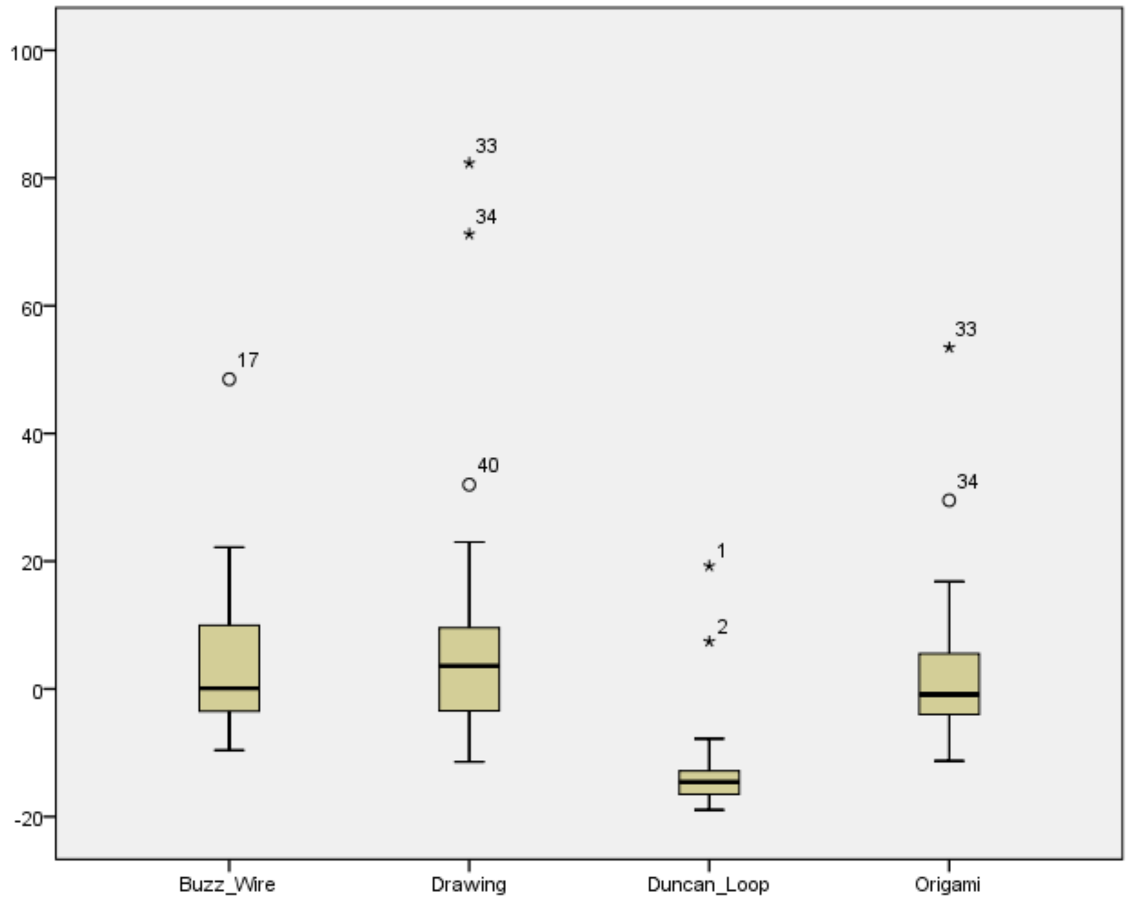

Figure 4. *Boxplots of the maximum performance on the tasks.*

The purpose of this research was to look for similarities on learning complex skills with other tasks. To see if any associations exist on the tasks, we did a correlation on the three parameters between the four different tasks. The Pearson's correlation was used on the three parameters, including the 95% confidence interval. In this research correlations are used to make predictions on prospective behaviour. For high-stake evaluations, like making predictions, a correlation of 0.8 or higher is needed (Fried & Feldman, 2008). To give an interpretation of the correlations, three levels of correlations are introduced:

High correlation - if the correlations is higher than 0.8.
Virtually irrelevant correlation – if the correlation lays between 0.6 and 0.8.
Absent correlation - if the correlation is under 0.6.

Table 4

Correlation and 95% CI on Previous Experience on the Tasks

	Buzz wire	**Drawing**	**Duncan loop**	**Origami**
Buzz wire	-			
Drawing	-0,063[-0.43, 0.40]	-		
Duncan loop	0.165[-0.52, -0.02]	0.001[-0.17, 0.29]	-	
Origami	0.092 [-0.39, 0.27]	-0.293[-0.14, 0.43]	0,034[-0.25, 0.45]	-

Table 4 shows the correlations between the tasks on previous experience. All the coefficients are close to zero and therefore match the category of *virtually absent correlation*, this means that no clear correlations can be seen between the tasks on this parameter. The confidence intervals are all considerably large, this means that the real correlations on these tasks could differ somehow. Most interesting are the correlations between Buzz wire and Drawing [-0.43, 0.40] and Duncan loop and Origami [-0.25, 0.45]. Both correlations could be under zero or close to 0.4, which is quite a difference.

Table 5

Correlation and 95% CI on Learning Rate on the Tasks

	Buzz wire	**Drawing**	**Duncan loop**	**Origami**
Buzz wire	-			
Drawing	0,390[0.14, 0.63]	-		
Duncan loop	0,258[0.02, 0.51]	0,109[-0.18, 0.44]	-	
Origami	0,021[-0.24, 0.27]	0.160[-0.09, 0.47]	0,081[-0.02, 0.23]	-

Table 5 shows the correlation on the learning rate, the slope of the learning curve. Also on this parameter, all correlations fit in the category of *absent correlation*. Interestingly the confidence intervals are all somewhat large, except the correlation between Duncan loop and Origami. The largest interval is between Drawing and Duncan loop [-0.18, 0.44]. Most interesting is the CI between Buzz wire and Drawing [0.14, 0.63]. This correlation (0.390) seems to fit in the category of *absent correlation*. However, according to the CI, this could possibly be up to 0.63 and therefore fit in the second category of *virtually irrelevant correlation*.

Table 6

Correlation and 95% CI on Maximum Performance on the Tasks

	Buzz wire	**Drawing**	**Duncan loop**	**Origami**
Buzz wire	-			
Drawing	0.066 [0.20, 0.36]	-		
Duncan loop	0.043[-0.25, 0.27]	0.026[-0.12, 0.27]	-	
Origami	0.033[-0.17, 0.38]	0.852[0.44, 0.94]	0.165[-0.05, 0.44]	-

The correlation on the third parameter, the maximum performance, is shown in table 3. Here again most of the coefficients are close to zero and imply *absent correlation*. Some of the correlation intervals on this parameter are moderately high as well, e.g. between Buzz wire and Origami [-0.17, 0.38]. Apparent is the correlation between Origami and the Duncan loop, which is 0.852, with a CI [0.44, 0.94], this fits in the category of a *high correlation*. The correlation between Drawing and Origami is also visible in figure 2. The CI shows that it is not certain that this is the actual correlation. This could lay a bit higher, up to 0.94. Or down to 0.44. The latter would mean that this correlation would not fit in this category anymore, but in *virtually irrelevant correlation* or even *absent correlation*.

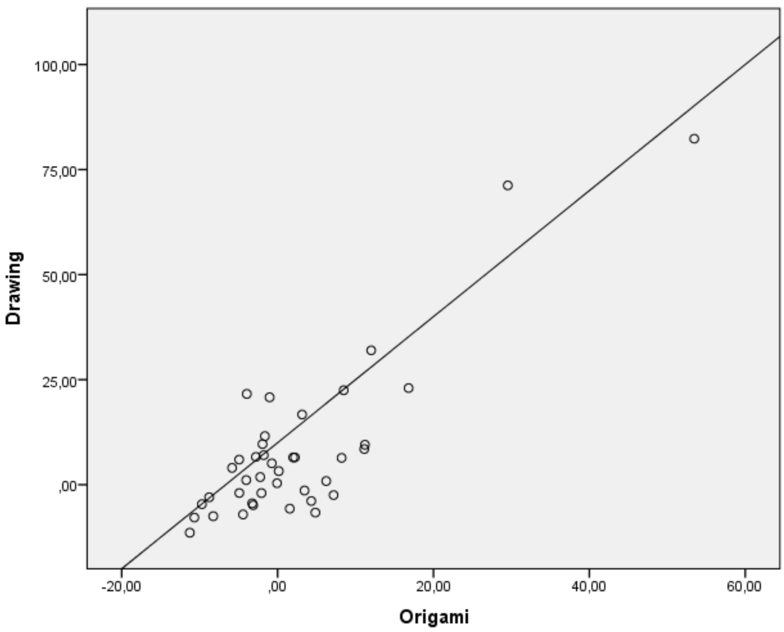

Figure 3. *Correlation between Drawing and Origami on Maximum Performance*

Discussion

The results show almost no correlations between the four tasks. On previous training and learning rate no relations were found at all. On the maximum performance only between Drawing and Origami a high correlation was found. This means that no clear associations were found between all four of the tasks and not on all parameters. These findings have two facets. First, no association can be seen between all four tasks. So it cannot be said that these tasks are all related to each other. Second, no associations were found on previous training and learning rate. Both will be explained below.

No association was found between all four of the tasks. This means that in this research no evidence was found that these tasks have something in common in the way people learn them. Therefore, it cannot be concluded that the holistic view is the good way of looking to this topic. Since, it is not found that is possible to make predictions on these tasks.

Only on maximum performance a correlation was found between tasks. On previous experience and the learning rate nothing striking was found. This could mean that the way people learn a dexterity task is not predictable by other tasks. The only thing we can possibly predict is how someone will perform a task in the end. But we do not know how the learning process will go and how long this will take. Then it just depends on the talent someone already has on this skill.

This research shows that, at least, three different skills exist which cannot be used to predict the other skills. Drawing and Origami correlate in maximum performance and could be based on a common underlying skill. The Duncan loop and the Buzz wire do not correlate with anything and are likely to be both based on other, separate skills. Possibly more than these three skills do exist as well. What is interesting in the two correlating tasks is that both were mental challenging, but the dexterity part was less essential. Drawing and folding paper are skills that are used by most people in their daily life regularly. The way the participants had to use these skills differed from their general use. The other tasks, tying a knot and the buzz wire are probably not used regularly by most people. These two tasks were not solely mentally challenging, but the participants had to get used to the skill as well.

What we expected to find in this research was a correlation between the dexterity tasks. The results show that this cannot clearly be found with this design. One possible cause for this could be that the underlying, shared skill for dexterity tasks does not give the greatest impact on the learning process and therefore is not shown in the results. Possibly this is too weak to give associations on dexterity. The results create an impression that multiple other skills play a role too in the way someone learns these tasks and therefore no associations can be found here. This can be conformed with literature (van Hove, Tuijthof, Verdaasdonk, Stassen, & Dankelman, 2010), where it was found that different forms of skill assessment are appropriate in different situations. Thus, only if the right skills are examined this can be used to make predictions. In research of Bann & Darzi (2005) it is stated that dexterity tasks are successfully used for selection in other fields. In MIS this has not yet succeeded, often due to methodological errors. The fact that it has often been useful is contradictory to our findings, but indicates that it is still possible that positive results will be found on this holistic approach in the future.

There are some consequences if the way people learn a task does not predict how they learn other tasks. It may be possible to say something about the end performance someone will reach on the task, which is very valuable. If this also works on predicting MIS, this can be taken into account when selecting people for the training. However, it is for the field of surgery an unsatisfactory outcome that still no ideal way is found for predicting the learning rate by examining dexterity tasks. Research of Mason, Ansell, Warren, & Torkington (2013) states that predictions on dexterity skills is possible. However, in surgery, only 25% has to do with dexterity, the other 75% with decision-making. This implicates that this method is possibly not sufficient for making predictions in MIS. Therefore, it is interesting is to look at other alternatives, such as using Virtual Reality. Multiple articles (e.g. Akhtar, Chen, Standfield, & Gupte, 2014; Sinitsky, Fernando, & Berlingieri, 2012)) initiate a new way of learning and assessing MIS using Virtual Reality. In this way assessment of new trainees would come the closest to real MIS, without having all the risks.

This research does come with some limitations as well. First, the learning process is not a homogeneous process, the learning rate changes from moment to moment. For example, at some points the participants changed their strategies, resulting in short periods of reduced performance. This is not included in the analysis, where the learning curve is seen as a gradual process. Also, during the research a lot of noise is probably measured as well. This can be due the lack of motivation or concentration during some of the trials by the participants. The lack of motivation was clearly visible by some participants when they get frustrated for failing several times in a row. Second, the participants did vary a lot in performance on the tasks. Some participants did the tasks a bit sloppy, others were very precise. What was observed by the researchers in the Buzz wire task was quite interesting. There tended to be some alternation between being precise or being quick. If the participants wanted to minimise the number of mistake the recorded time was higher, and vice versa.

Despite the fact that we did observe the performance on each trial, this is currently not taken into account. In future research this performance should be analysed as well.

Because no possible way of predicting the learning of laparoscopy was found until now, a turn was made in this research. Instead of looking at hypothetical factors, such as cognitive skills, the possibility of predicting tasks with other tasks was approached. This research showed only a correlation between two of the tasks and only on the maximum performance. Possibly the different dexterity tasks had to do with different underlying skills and therefore they did not correlate with each other. In further research multiple other tasks can be added to check whether this is the case and if associations can be found between other tasks. When these associations will not be found, they possible will not be found on MIS either. Thus, since the two most desirable ways of predicting MIS both do not seem to be working. That is, prediction by the use of the components and prediction with other complex motor procedures. It appears that prediction of MIS would only be possible with MIS itself. This would speak for an alternative; the use of Virtual Reality in this field. Where predicting MIS with virtual reality simulators could be examined, since this option is still safer and cheaper than MIS itself.

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Appendix

Appendix 1 – Question form

General Question (at the begin of the study):

Age:

Gender:

Nationality:

Study/Profession:

Are you left- or right handed or does that change? (think about: writing, using scissors, cutting, throwing)
How do you feel about working with your hands? (think about crafts/repairs)
Do you get easily frustrated while working with your hands?

Experience Question (directly after task):

Do you have previous experience with (this task)? If needed, give examples

Questions at end of the test (pay attention to the order of the tasks the participant got during the study):

Which task did you like? Which tasks were hard?

Ask about the performance (this question should be answered after every task).

How would you estimate your performance at the beginning? (on a scale from 1-7, 7 is good performance, 1 is bad performance)

How would you estimate your performance at the end? (on a scale from 1-7, 7 is good performance, 1 is bad performance)

Appendix 2 – Observation form

Participant number: Researcher:
Task:

Trial number	Time	Errors	Coding	Comments
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15				
16				
17				
18				
19				
20				

Appendix 3 – Instructions tasks

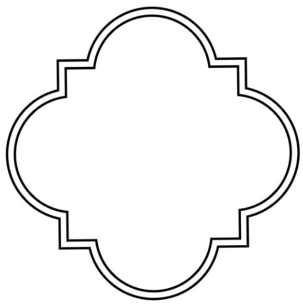
DUNCAN LOOP

Take the rope and try to replicate the knot shown on the paper. Make sure you follow the instruction and do this as fast as possible. When you are ready the clock will start. And when you finish, announce this to the researcher so the time can be stopped. You are going to make this knot 10 times. If you have any questions you can direct these to the examiner.

Duncan loop

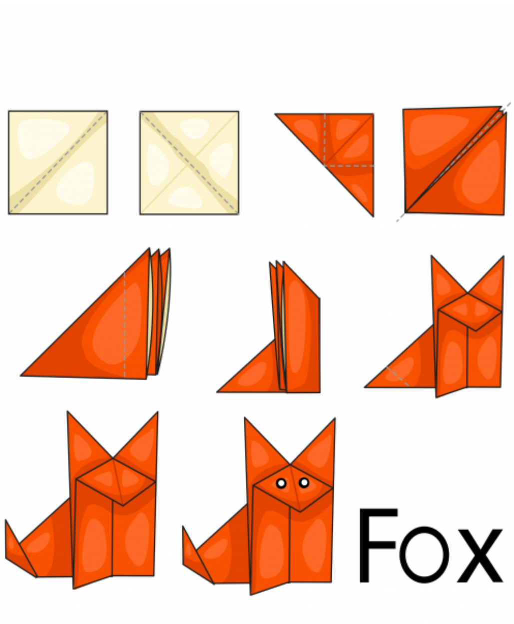
MIRROR DRAWING

In this experiment you will be tracing a shape, but instead of looking at your hands, you are going to look in a mirror. Try to stay in between the lines and to finish as fast as possible. You must start at the same point every time. If you have any questions you can direct these to the examiner.



ORIGAMI

Take a piece of paper and follow the steps of the instructions below to build the fox. Try to make the fox look like the fox in the instruction, however you must do this as fast as possible. When you are ready the clock will start. And when you finish, announce this to the researcher so the time can be stopped. You are going to make 20 foxes. If you have any questions you can direct these to the examiner.



BUZZ WIRE

In this experiment you will completing a buzz wire task. Take the staff and try to follow the wire as fast as possible. Time on task and errors will be measured.

Appendix 4 - Syntax data analysis

```
DESCRIPTIVES VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /STATISTICS=MEAN STDDEV MIN MAX.

EXAMINE VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /COMPARE VARIABLE
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL
  /MISSING=LISTWISE.

DATASET ACTIVATE DataSet3.
DESCRIPTIVES VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /STATISTICS=MEAN STDDEV MIN MAX.

EXAMINE VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /COMPARE VARIABLE
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL
  /MISSING=LISTWISE.


DATASET ACTIVATE DataSet4.
DESCRIPTIVES VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /STATISTICS=MEAN STDDEV MIN MAX.

EXAMINE VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /COMPARE VARIABLE
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL
  /MISSING=LISTWISE.
```

```
DATASET ACTIVATE DataSet1.
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES INPUT=Buzz_Wire Drawing Duncan_Loop Origami
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=1000
  /MISSING USERMISSING=EXCLUDE.
CORRELATIONS
  /VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

DATASET ACTIVATE DataSet3.
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES INPUT=Buzz_Wire Drawing Duncan_Loop Origami
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=1000
  /MISSING USERMISSING=EXCLUDE.
CORRELATIONS
  /VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

DATASET ACTIVATE DataSet4.
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES INPUT=Buzz_Wire Drawing Duncan_Loop Origami
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=1000
  /MISSING USERMISSING=EXCLUDE.
CORRELATIONS
  /VARIABLES=Buzz_Wire Drawing Duncan_Loop Origami
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.
```