PHYSICAL INTERACTION MAPPINGS: UTILIZING COGNITIVE LOAD THEORY IN ORDER TO ENHANCE PHYSICAL PRODUCT INTERACTION

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Abstract

Learning to physically operate traditional products can be viewed as a learning process akin to any other. As such, many of today's products, such as cars, boats, and planes, which have traditional controls that predate modern user-centered design techniques may be imposing irrelevant or unrelated cognitive loads on their operators.

The availability of working memory has long been identified as a critical aspect of an instructional design. Many conventional instructional procedures impose irrelevant or unrelated cognitive loads on the learner due to the fact that they were created without contemplation, or understanding, of cognitive work load.

The goal of the research was to investigate the fundamental relationships between physical inputs, resulting actions, and learnability. The results showed that individuals can quickly adapt to input/output reversals across dimensions, however, individuals struggle to cope with the input/output when the dimensions are rotated due to the resulting increase in cognitive load.

Keywords: Cognitive load theory, Instructional design, Product interactions, Design theory, Design cognition

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Please cite this paper as:
Surnames, Initials: *Title of paper*. In: Proceedings of the 20th International Conference on Engineering Design (ICED15), Vol. nn: Title of Volume, Milan, Italy, 27.-30.07.2015

1 INTRODUCTION

Instructional design is the process of designing instructional experiences, such as e-learning, with the goal of making the attainment of knowledge, and skill, more functional and appealing. Attention has been brought to the parallel of instructional and product designers as they both share the common goals of developing solutions that are effective, efficient, and appealing.
The availability of working memory has long been identified as a critical aspect of instructional design. Cognitive Load Theory (CLT) (Sweller et al., 1998, Sweller, 1988, Sweller et al., 2011, Mousavi et al., 1995) dictates that incorrect instructional procedures raise cognitive load through imposing needless additional workloads on the available working memory. Mousavi et al (1995) elucidate that CLT is based on the following understanding of the brain's cognitive architecture:

- The brain has a finite amount of working memory which is only capable of holding and processing a small amount of information at any given time.
- The brain has an abundance of long term memory which is for all intents and purposes infinite in size.
- Schema construction is a principal learning mechanism.

Sweller (1994) explains that schemas are cognitive structures which consist of organized elements of information and their interrelationships. The brain utilizes schemas to organize current knowledge which provides a basis for interpreting new information. Schema are stored in the long term memory and allow individuals to recall groups of information as individual entities. This allows the brain to process multiple of elements as a single unit, reducing cognitive workload. Contemplate how the brain groups everyday objects, for example cars, once the car schema has been created it is trivial for the brain to identify a car regardless of whether the car is new to an individual. Ultimately, the brain has the ability to handle a potentially unlimited variety of objects that are encompassed by the car schema. Schemas are utilized across academic and social learning, and schema generation, and modification, is an ongoing constant throughout life. Sweller maintains that the challenge associated while learning new tasks can vary radically, regardless of the perceived complexity of the task. i.e. two tasks my appear to contain an equal amount of information and complexity but the associated effort may contrast immensely. Ultimately the degree of available working memory is the defining factor regarding the ease of schema generation.
Paas et al. (2003) maintain that many conventional instructional procedures impose irrelevant or unrelated cognitive loads on the learner due to the fact that they were created without contemplation, or understanding, of cognitive workload. Consequently, there is now a vast area of research in regard to instructional design aimed at applying processes and principles in order to reduce extraneous cognitive load whilst learning because extraneous and task specific cognitive loads are additive. Therefore removing irrelevant workloads frees up cognitive space which can then be utilized to complete the instructional task.
Learnability refers to the ability of a product, or system, to facilitate the user in the learning of operation. The learnability and usability of a product need not be mutually exclusive as learnability is a subset of usability. Consequently increasing the learnability of product will have a direct positive effect on the usability of the product.
Usability refers to ease of use and learnability of a human-made product. There now exist vast fields of study such as 'User Centered Design' (UCD) in which the requirements and limitations of the end users are considered from the outset and are a critical aspect of the design process. However, even after employing such principles it still remains challenging for designers to understand and envisage the vast array of user requirements. Furthermore, concepts such as UCD are relatively new, arising in the 1980s. Therefore, many of today's products, such as cars, boats, and planes (the focus of this paper), are still fundamentally operating using controls and physical inputs which predate modern design techniques.
In addition, given that CTL is a relatively recent development, it seems fair to conclude that many such products were also created without the contemplation, or understanding, of cognitive workload and therefore their fundament control systems may be imposing extraneous cognitive loads on individuals whilst they are learning how to operate them. While individuals may feel that such products are intuitive to operate there is evidence to the contrary. The average individual requires 47

hours of lessons and 22 additional hours of practice to pass their driving test (The AA, 2014). This is nearly the same amount of time, 70 hours, required for an individual to acquire a private pilot's license so it is clearly not a trivial task (AOPA, 2014). Therefore, while individuals may now feel that such products are intuitive, this may be a result of bias from the perception of a user that now knows how operate the product.

Regardless, the design history of such products coupled with the lack of research in regard to the suitably of their control systems accentuates the need to investigate the impact of control inputs and operations on the learnability and usability of products. The purpose of this paper is to investigate the relationship between learnability, usability, and cognitive load: Based on the hypothesis that reducing the cognitive load associated with physical product interaction will result in increased learnability and therefore usability of the product.

2 COGNITIVE LOAD

Instructional Cognitive load (Sweller et al., 1998, Sweller et al., 2011, Sweller, 1994, Paas et al., 1994, Paas, 1992, Paas and Van Merriënboer, 1994) spans multiple dimensions and represents the overall load imposed on the cognitive system during the undertaking of a task. The factors affecting cognitive load can be divided into two categories: causal factors and assessment factors; where causal factors are factors that influence the cognitive load and assessment factors are influenced by the load. The causal factors encompass variables such as subject and environmental characteristics and their subsequent interactions. Subject characteristics are a relatively stable characteristics which relate to the individual carrying out the task, for example cognitive capabilities and experience. Environment characteristics relates to elements such as room temperature and background noise. Task characteristics include the type of task, the associated reward, for example time constrictions etc. Task interactions can also be influenced by unpredictable factors such as motivation and performance spikes. Cognitive load (Fig 1) can be conceived through grouping variables into the following three dimensions:

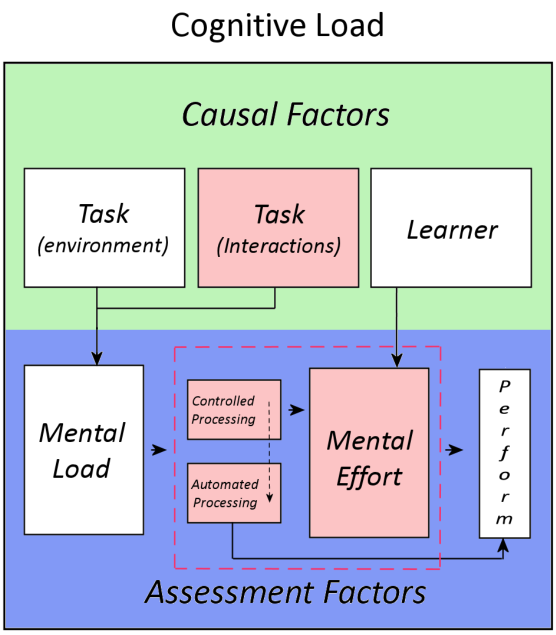

Figure 1. Cognitive Load Schematic adapted from Paas & Merrienboer, 1994

- Mental load - Mental load is the total load imposed by the environment and the task. Mental load is a task specific constant which is unrelated to individual's abilities or characteristics.
- Mental effort - Mental effort refers to the amount of cognitive processing an individual undertakes while carrying out a task. Mental effort is subject to the above mentioned causal factors.
  - Controlled processing - Controlled processing is processing that is consciously controlled by the brain. For example when one has to concentrate on a task and they are consciously aware of thoughtful effort.
  - Automated processing - Tasks that are automated by the brain and carried out without mental effort. As individuals become accustomed to a task controlled processing can become automated processing allowing the user to carry out the task with a reduced mental effort.
- Performance - Performance is an expression of the success of an individual in regard to the goal of the task. Performance is a reflection of the mental load, mental effort and the learner, therefore performance is subject the causal characteristics.

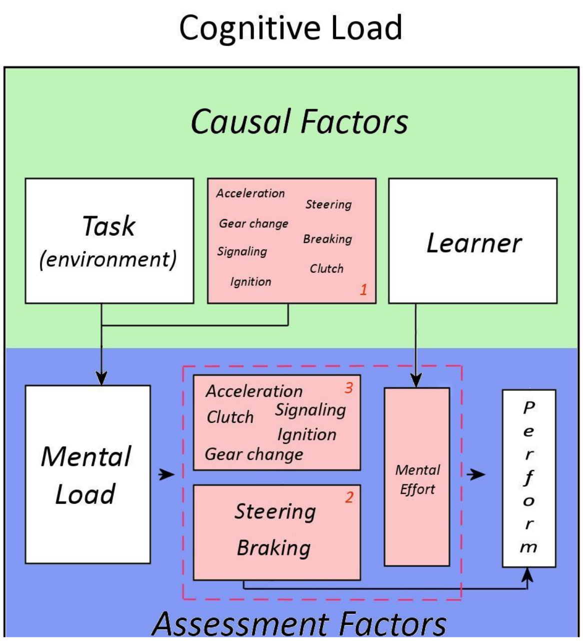

Figure 2. Interactions traced through the Cognitive Load Schematic

Paas and Van Merriënboer (1994) explicate that mental load, mental effort, and performance are all components of cognitive load, where mental load is a reflection of the task only and mental effort and performance are influenced by all the causal factors. Mental load is a construct of the task environment and task interactions, and is consistent to a task. Mental effort reflects the total cognitive resources that are actually applied to task completion, hence mental effort is the critical aspect controlling task completion. Indeed the degree of mental effort required whilst undertaking a task is considered to be the nucleus of cognitive load. Consequently, mental effort can be utilized to provide an effective measurement of cognitive load.

Take the example of someone who already knows how to cycle, learning to operate a motorcycle. Several of the controls and interactions involved in operating a motorcycle overlap with the controls and interactions which are used to operate a bicycle, for example steering and braking. However, other interactions are unique to the motorcycle, for example changing the gears and signalling. In order to understand how the familiarity of interactions can affect the learning process the interaction types can be traced through the cognitive schema diagram (Fig 2):

1. Box one shows some of the operation aspects of the task/user interactions. The contents of the box refer to the interactions required to carry out the named task, for example acceleration refers to turning the acceleration on the handle to accelerate the motorcycle. The three causal factors (task environment, task interactions, and learner) combine to influence the overall cognitive load. The task environment and the task/user interactions combine to produce the total mental load of a task, while the learner characteristics influence the mental effort (The mental effort is interconnected with controlled and automated processing). The task environment and leaner variables have not been examined throughout the diagram so as to trace just the just the physical interactions.
2. Box two shows the interaction aspects of the task that the user is already familiar with through operating a bicycle (automated processing). The user already knows how to steer and brake the motorbike as they are direct emulations of riding a bicycle. Consequently, the schemas for such actions already exist within the user's brain. As previously discussed the brain does not have to apply any cognitive resources to automated processing.
3. Box three shows the aspects of the task that the user is not familiar with and therefore has to apply cognitive resources to carry out (controlled processing). The degree of familiarity may vary, for example learning to operate the ignition switch compared to learning to change gears. Under such circumstances the user may be able to alter existing schema or may have to construct totally new schema. As the user becomes familiar with the product they start to form schema to govern the interactions shown in box three. The end result of the process is the controlled processing becoming automated processing, i.e. those aspects moving from box three to box two.

It is the position of this paper that, depending on the situation, certain types of interactions may either increase or decrease the learnability of a product due to how quickly the interactions can be moved from controlled to automated processing.

Cognitive Load Theory presents a framework which can be utilized by instructors in order to reduce cognitive load through controlling, and manipulating, task conditions and instructional materials. CLT provides empirical guidelines that allows instructors to reduce extraneous cognitive load therefore optimizing the available working memory for learning. (Van Merriënboer and Ayres, 2005)) further explain that CLT differentiates between three types of cognitive load: intrinsic cognitive load, germane cognitive load, and extraneous cognitive load.

Intrinsic cognitive load relates to the immanent difficultly of the subject under instruction, for example the difficultly of mathematical addition in comparison to complex equations. The inherent difficultly of such tasks cannot be altered by the instructor; however the tasks can be broken down into schema which can be taught then combined to provide an understanding of the problem as a whole.

Extraneous cognitive load is a load that is not essential for undertaking or learning a task. Extraneous cognitive loads can be imposed by such things as bad teaching practices, substandard problem solving techniques or poorly designed and inadequate environments. For example, extraneous cognitive load could arise when an instructor is describing a product to a student. A product could be described using either visual mediums, verbal mediums, or a combination of both. If the instructor selected to describe the appearance of a product using only the verbal medium clearly that would be a far less effective method than simply showing the student a picture. The verbal method would load the student with irrelevant and unclear information; this redundant cognitive load would be classified as extraneous. Due to the fact that the brain has limited cognitive resources CLT dictates that extraneous cognitive loads must be reduced in order to optimize the free cognitive space for intrinsic and germane cognitive loads.

Germane cognitive load is the load which is devoted to the processing, formulation, and automation of schemas. Germane load is considered to be a constant which cannot be directly influenced by an instructor. However, Merrienboer, Sweller and Pass consider reducing extraneous load and freeing up the available cognitive load for the germane load to be a critical aspect of CTL. Indeed the development of schema and the movement of load from controlled processing to automated processing is the very basis of learning. If learning scenarios can be effectively manipulated in the described manner the associated learning curve will be reduced.

Learning to operate products is a learning process like any other and there are instructional situations during such learning, for example driving lessons, where CTL could be applied in a traditional sense. However, most product operations are not introduced under the guidance of a tutor, and even if products are learnt under instruction the physical design of the product remains fixed. The physical design of a product controls the manner in which the users interact with a product while carrying out a product related task; and interactions have already been highlighted by Pass & Merrienboer as a causal factor. Not all interactions are created equally, for example, analogue control offers a wider degree of freedom than digital.

Given the vast array of controls, inputs, and functionality of products there is obviously a disparity in the complexity and learnability of products. CTL affirms that an instructor can reduce learning curves thought proper teaching practices, problem solving techniques and adequate environments. It is the position of this paper that the same principles can be applied to product design, where the designer takes the role of the instructor seeking to reduce learning curves though optimizing product manipulation in order to reduce extraneous cognitive loads.

3 EXPERIMENT

An experiment was designed to explore the relationship between inputs, resulting actions, and learnability. The aim of the research was to understand the relationship between interactions and resulting actions at a fundamental level. Consequently, the purpose of this research is to investigate whether modifying the mappings of product interactions can reduce cognitive load and consequently increase product learnability.

The experiment was based on the premise that learning to operate a product is no different than any other learning process and is therefore subject to cognitive learning theory, i.e. modifying a product to reduce cognitive load should result in increased learnability. Consequently, the goal was to understand whether altering the mapping of inputs and resulting actions can affect cognitive work load.

3.1 Subjects

The participants were 31 adults (23 male, 8 female) from the following aged between 21 and 76. As an incentive to concentrate on the task the individual with the best high load performance (time wise) received a £20 book voucher. While this added an element of pressure, it was felt that providing an incentive was important to motivate participants and ensure that they were maximizing their cognitive effort.

3.2 Environment

The environment consisted of a simple 2D computer game, Pac Man. The user controlled the navigation of the Pac Man though a 2D maze like environment. The goal of the game was to navigate the maze and collect pellets. Traditional Pac Man includes ghosts which were removed for the experiment so as not add an additional cognitive load. The maze did have a start and finish point, consequently the goal of the game was not simply maze navigation, removing the impact of route memorizing. The game was controlled using 4 simple inputs, the arrow keys.

3.3 Instruction

General instruction regarding goal, and the controls, of the game was demonstrated to the users prior to the experiment. The users were given up to five minutes to get accustomed to the controls. Completion of a single level under normal conditions takes approximately one and a half minutes.

3.4 Design

The experiment consisted of three scenarios aimed at adapting the control inputs in order to change the level of mental effort required to complete the task.

3.5 Scenarios

3.5.1 Scenario One

In the first scenario the users were asked to navigate the maze using the normal input controls. The users were given three attempts to complete the game; the average measurements were then recorded. The initial scenario was based on the premise that users will be familiar with controls of scenario one, the purpose of giving the users three attempts was to reduce the influence of factors outlined by Paas et al (1994), such as performance spikes and dips. Performance spikes refer to situations where an individual generates an untypically good result, for example a poor player getting a strike in ten pin bowling. Performance dips refer to good player generating an untypically poor result.

3.5.2 Scenario Two

In second scenario the users were asked to complete the game five times using reversed controls, i.e up swapped for down and left swapped for right. The users were given no time to learn the new controls as aim was to capture the learning curve as part of the experiment. The aim of scenario two was to investigate the impact of changing the controls across an axis/dimension.

3.5.3 Scenario Three

In third scenario the users were asked to complete the game five times using controls which have been rotated ninety degrees. Again the users were given no time to get used to the controls in order to capture the learning curve. The aim of scenario three was to investigate the impact of mixing the controls and axis/dimensions.

3.6 Data Capture

After each experiment the following data was captured:

The length of time taken to complete the course as a direct measurement of performance. As explained by Plass et al. (2010) currently the most utilized objective method of examining cognitive load is performance based analysis.

The users were asked to provide a subjective measurement of task difficulty (mental effort) after every completed level. The measurement consisted of the users scoring the tasks on perceived difficulty on a scale of 1-7, ranging from exceptionally easy to exceptionally difficult. Ayres (2006) reveals that such an approach can produce highly reliable results where errors and performance are correlated to perceived complexity.

3.7 Procedure

All experiments took place with the participant in solitude so to as to avoid any task environment influences; instruction was provided regarding the controls only, then the instructor monitored the experiment from a distance. The participants were asked not to converse with the researcher unless it was unavoidable.

The users were asked to carry out scenario one and the computer recorded the total time taken to complete each task. On completion of scenario one the average time was recorded to serve as a benchmark for scenarios two and three. The users were also asked to complete the questionnaire for scenario one; the users were not aware of their times throughout the experiment to avoid the time serving as means for deducing difficultly. The approach of comparing the users' results from the preceding scenarios to scenario one removes the any potential for individual skill levels to influence the data, i.e. the users were competing against themselves therefore the skill factor was constant.

The users then completed scenarios two and three. Again, the only information the users were provided with prior to being asked to complete the scenario was the inputs. The computer recorded the times taken to complete every level and the users were asked to complete the questionnaire after every level.

4 RESULTS

The results of the study showed that the brain can cope with input/output changes on the same dimensions (for example swapping reversing the actions on the X or Y axis) but struggles to cope with input changes across different dimensions (for example swapping the actions of the X and Y axis). That is, as a group the participants by then end of scenario one had reached a similar average task completion time to the benchmark, just 7.5 seconds (or 10.7%) slower with a merging perceived difficultly; 81% of the participants rating the benchmark as very easy or easy, compared to 75% at the end of scenario one. Whereas, by the end of scenario two the average completion time was 73 seconds or (97% slower) with a 77% of the participants still rating the controls as hard or very hard. (For ease of use the times are displayed in decimal format in the visuals in the results section)

Based on the null hypothesis that there is no relationship between the controls and performance times, the standard score (z-score) can be calculated for each of task completion time. The z-score can then be cross referenced to the standard normal distribution table in order to calculate the probability that the modified control completions were due to chance:

Based on a P value of less than 0.01 in both cases, the null hypothesis that there is no relationship between the controls and performance times can be rejected.

4.1 Average Times

4.1.1 Scenario One

In both input change scenarios the average time per attempt generated inverse relationships where the time was inversely proportional to the number of attempts. In both cases similar relationships can be observed in the standard deviations and variances. The subjective measurements of task difficulty (mental effort) also generated inverse relationships where the perceived difficulty was also inversely proportional to the number of attempts. As demonstrated Ayres (2006) these results can be considered highly reliable as performance is correlated to perceived complexity.

4.1.2 Scenario Two

The average time results generated by scenario two shows an inverse relationship where the difference in the time intervals decreases throughout the experiment, i.e. the time improvement between attempt one and two is greater than the time improvement between attempt two and three, with the users reporting correlating decrease in mental effort. In regard to CLT this is exactly what we would expect to observe; where the brain is altering the original schema and transferring the operations from controlled to automated processing.

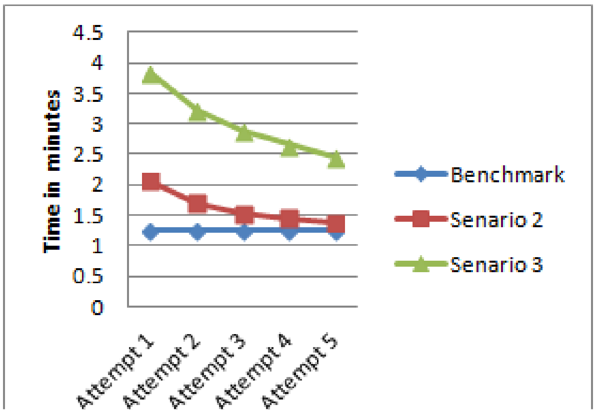

Figure 3. Average time of benchmark and all scenarios.

However, the same trend is not observed in the standard deviation and variance where it stays relatively static between attempt one and two, and then decreases. After a deeper investigation of the results this initial plateau can be explained through the causal factor the learner, in this case learner skill and the extra time some of users took to adapt to the controls: 33% of the users failed to decrease their time by 10% or more between attempt one and attempt two, compared to only 6% of the users failing to drop their time by 10% or more between attempt two and attempt three. This suggests that some of the participants took a longer time to adapt to the new controls than others. A similar trend can be observed at the end of the experiment between attempt four and attempt five. Again this can be explained learner skill where the results revealed that 16% of the users did not manage to get within 20% of their benchmark time. In contrast 52% of the participants managed to get a time within 10% of their benchmark time.

4.1.3 Scenario Three

The average times generated by scenario three show a substantial increase over scenario two with the initial average time increasing by 206.67%, then following the same inverse relationship as scenario two where difference in the time intervals decrease throughout the experiment. A plateau in the standard deviation and variance can also be observed in scenario three between attempt 4 and attempt 5, again this can be explained by variation in participant skill levels. Many of the users struggled during scenario three with only 42% of the users managing to record a time under 2.30 and the times varying during the fifth attempt from a best time of 1.32 to a worst time of 3.48. Furthermore, 20% of

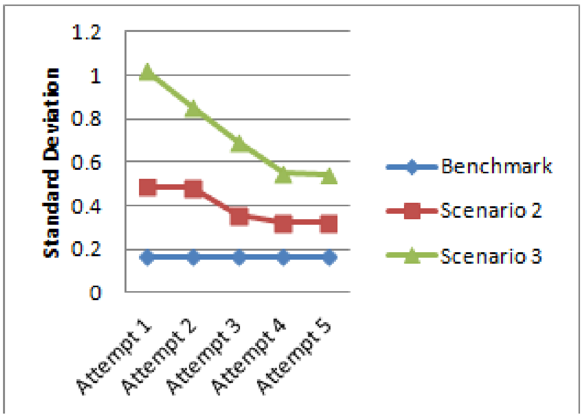

Figure 4. Standard deviation of benchmark and all scenarios.

the users did not record their best time on last attempt and 61% of the users recorded a jump in time during succeeding attempts some point throughout the experiment. Jumps in time were also recorded in scenario one however invariably they occurred once the individuals were recording fast performance times and therefore can be explained through path section as opposed to learnability and mental load.

4.2 Perceived Difficulty

The perceived difficulty (mental load) of the three scenarios was highly correlated to the average performance times. However, although the average times vs. the perceived difficult shows a straight forward relationship with matching inverses relationships to the performance times, a more in-depth analysis of the data reveals some interesting results. As previously mentioned the participants were not shown their time during the experiment to avoid providing them with an objective measurement by which they could gauge difficulty. Of the 61% of users that recorded a jump in time during scenario

three 37.5% of them simultaneously recorded a decrease in difficulty. A similar trend can be observed throughout scenario one however it does not appear to be for the same reason.
In scenario one the participant times rapidly reached the bench mark time then started to level out. Nonetheless, the users still reported a decrease in perceived complexity. This can easily be explained by CLT as individuals can add additional mental effort in order to compensate for an increase in mental load. As the individual gets accustomed to a task the performance level will stay the same but the required mental effort will decrease. The critical aspect being performance time; if there is room for improvement then the mental load will stay relatively high, as seen in attempt one & two while the performance increases. Only when the room for improvement diminishes does the performance stay the same while the mental effort drops off. In this case the recorded drop in mental effort would seem to be a result of movement from controlled processing to automated processing, which is supported by the fact that the mental effort has reduced to the easier rated side of the scale. The same explanation cannot adequately explain the results generated in scenario three. Firstly, the performance times were not even close to the benchmark time, nor were they levelling out. Secondly, the perceived difficulty was not dropping off, in fact it was still firmly within the very hard/hard range. A possible explanation for this is a perception of learning; the very act of practicing the inputs generates a perception that the individual must be improving, even if they are not. This explanation would also explain the difference between perception and time when the two scenarios are directly compared. For attempt five in scenario three has an average completion time of 2.28 with 75 % of the users rating it hard or normal. Whereas, attempt 2 in scenario two has a similar perception rating with 77.5% of the users rating it normal or harder yet is has a drastically superior performance time of 1.42.
Such results lend support to the earlier argument that products which were created without contemplation, or understanding, of cognitive work load may contain fundament control systems which impose extraneous cognitive loads on individuals whilst they are learning how to operate them. While individuals may now feel that such products are intuitive, that is a result of bias based form the perception of a user that now knows how operate the product.

5 CONCLUSION

This paper argues that cognitive load theory can be utilized by designers to enhance product interaction as the design of product interactions has a direct bearing on the cognitive load of the operator. More specifically, certain types of interaction mappings may either increase or decrease the learnability of a product due to how quickly the interactions can be moved from controlled to automated processing.
An experiment was carried in order to demonstrate how cognitive load theory could be applied to product design and to investigate the relationship between inputs, resulting actions, and cognitive load. The findings of this study demonstrate that even at the most fundamental level the selection of inputs and resulting outputs can have substantial influence on mental effort and learnability. Consequently, since many product's control systems predate modern design techniques they may not be optimally mapped and are therefore imposing extraneous cognitive loads on the operator.

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