Development of a virtual experiment to validate the relationship between engineering changes and learning curves using design structure matrices

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Abstract: The increased demand for high-performing engineered products pushes manufacturing firms to introduce novel and more complex products at an ever-faster pace. This invokes major engineering changes in these firms. The resulting disruptions to manufacturing performance and efficiency losses are poorly understood. This paper proposes a virtual experiment that validates the relationship between engineering changes that cause changes to the production process and the manufacturing cycle time learning curve. Product complexity and product commonality are identified as parameters of engineering changes that affect the learning curve. These parameters are quantified using design structure matrix methods. The effects of product complexity and commonality on the manufacturing learning curve are tested using an experiment. The results of this study can be used by management professionals to mitigate risks and improve resource allocation after engineering changes.

Keywords: learning curve, product complexity, design structure matrix, product commonality, manufacturing cycle time

1 Introduction

Over the past few decades, there has been a push towards continuously introducing novel and more complex products in manufacturing plants worldwide. This trend is driven by several factors, including the demand for more customized and specialized products, the integration of innovative technologies and the need to meet increasingly stringent regulations and standards. As the demand for high-performing engineered products often increases their complexity (Arthur, 1993), manufacturing plants are forced to produce these increasingly complex products at an ever-faster pace, creating organizational challenges (Anderson and Joglekar, 2012; Lindemann et al., 2009; Wiendahl and Scholtissek, 1994). One of these challenges is how manufacturing plants can forecast resource planning after the introduction of such a novel complex product.

This study builds upon the study of Dooper et al. (2022) in which they examined the forecasting of learning curves after an engineering change using product complexity. A learning curve is a mathematical representation of the change in a performance indicator as a function of experience. When a new or redesigned product is introduced (e.g., engineering change), the manufacturing of the first unit takes more time and resources compared to the following unit. This increase in manufacturing cycle time (MCT) is identified in the learning curve as an uptick, which was first observed by Wright (1936). However, this uptick is not constant for each product introduction as some have a significantly higher uptick compared to others. Dooper et al. (2022) proposes that there is a correlation between change in complexity of the system architecture and the amount of uptick of the MCT of a product. However, these factors and their relationship with learning curves in MCT have not yet been extensively studied (Dooper et al., 2022).

The aim of this study is to further explore the relationship between metrics quantifying engineering changes that cause changes to the production process, such as product complexity and product commonality, and their correlation with parameters in learning curve models. Knowledge about how these metrics impact the learning curve could help both industry and academia with understanding the mechanisms driving organizational learning during the introduction of new products. This study in particular aims to develop an experiment that enables the isolation of factors driving product complexity and product commonality and assesses their impact on the overall learning curve of MCT. So the study considers in particular engineering changes that imply a modification to a product after that product has entered production (Jarratt et al., 2011) and seeks to relate this modification to the manufacturing cycle time learning curve.

Exploring the relationship between engineering changes and learning curves adds to the existing organizational learning literature and aims to connect multiple academic fields, such as systems engineering, industrial engineering, and operations management. Unraveling this relationship could alleviate some of the difficulties in resource planning after a company introduces new products to its manufacturing lines. The developed experimental framework will help estimate the impact of product changes on MCT which can be used in practice.

2 Theoretical Background

2.1 Learning

Learning is central to how we as humans develop ourselves and adapt to situations we face. This is why learning has received much attention in several academic fields, such as psychology, evolutionary theory, behavioral ecology, neuroscience, and even computer science (Barron et al., 2015). Despite its prevalence in the existing body of literature, academics struggle to explicitly define what the concept of learning means. Most proposed definitions vastly differ within and across research fields (De Houwer et al., 2013). To explore learning in organizations, a clear functional definition of learning needs to be formulated.

To define such a functional definition, one must first specify the period in which learning takes place. For this study's purposes, learning is seen as an ontogenetic adaptation of an individual organism to its environment during its lifetime (Skinner, 1984). Our functional definition of learning is based on previous work that aims to tackle this concept's broad and abstract nature without trivializing its complexity (De Houwer et al., 2013; Fiol & Lyles, 1985; Kim, 1998). This study's functional definition of learning is: *"Increasing one's capacity to take effective action as a result of gained experience."*

While this functional definition only covers some aspects in defining an explicit description of learning, it allows for a focused view on the concept within this study's bounds. In this definition, effective action can be defined as the increase in performance and/or efficiency of a performed action. Gained experience refers to prior instances in which the individual has performed a similar action which it was able to observe and assess the outcomes of. Through this definition, we try to circumvent the complex nature of behaviors and focus on actions that specifically lead to measurable outcomes of a task.

Notwithstanding this functional definition of learning, the way one learns remains to be discovered. The functional definition states that an individual needs to gain relevant experience in a certain task to be able to learn. To explain how we gain and process experience, the Observe-Assess-Design-Implement (OADI) cycle of individual learning may be used (Kim, 1993). The cycle explains that an individual actively observes concrete actions and, consciously or subconsciously, assesses them by reflecting on their observations followed by designing an abstract concept which is a suitable response that the individual implements before the cycle starts over. In this cycle, two dimensions of learning are identified: operational learning and conceptual learning (Fiol & Lyles, 1985; Hedberg, 1981; Kim, 1993; Senge, 1998). Operational learning is the acquisition of 'know-how', which entails the ability to produce some action and thus describes learning on the procedural level. This can be manifested as learning steps to complete a specific task as efficiently as possible (Mukherjee et al., 1998). Conceptual learning can be categorized as 'know-why', which entails the ability to articulate a conceptual understanding of the experience.

Similar findings are presented in the study of Argote and Miron-Spektor (2011), which describes the flow of learning in organizations. Learning starts with experience in a certain task. When an individual is able to reflect and analyze this experience it converts into knowledge. From this new knowledge the individual can exercise a change in behavior which, when accurate, results in enhanced performance of a task. In the view of organizational learning, this knowledge may be shared among other members of the organization to facilitate collective learning. As the (individuals in an) organization continues to learn, it may experience learning curves, describing the rate at which an organization is able to improve its performance through learning from experience (Dutton and Thomas, 1984). The flow of learning is visualized in Figure 1.

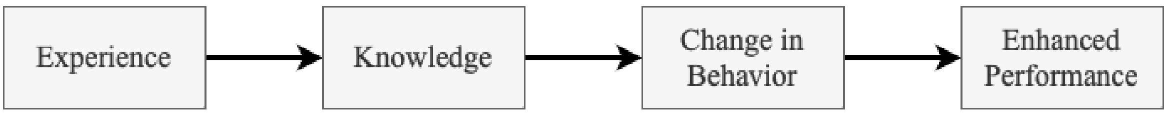

Figure 1. The flow of learning

2.2 Learning Curve

As described in the functional description, learning refers to an increase in performance (effective action) due to prior gained experience. The relationship between performance and experience can be quantified with a Learning Curve (LC). The use of LCs has proven to be an effective tool to monitor individual workers' performance when performing repetitive tasks, leading to a reduced process loss due to a lack of experience during the first production cycle (Argote, 2013; Dar-Ei, 2000; Jaber and Guiffrida, 2008; Salameh and Jaber, 2000).

An LC is a mathematical representation of a worker's performance on repetitive tasks. The LC graphically depicts how a process is improved over time due to learning, for example, reductions in MCT after more experience with the task. As these iterations occur, workers tend to lower assembly times due to familiarity with the task and their ability to form shortcuts and different, more effective, strategies (Dar-Ei, 2000; Wright, 1936). LCs have gained attention in various industries such as chemical, automotive, electronic, software and construction (Anzanello and Fogliatto, 2011). Since the introduction of the original log-linear model by Wright (1936), researchers have proposed alternate models to compensate for different economical segments, resulting in many univariate and multivariate models of varying complexity (Anzanello and Fogliatto, 2011). In practice, when working with performance data, such as assembly time, the exponential and power-law models can be used to build a more elaborate model that can include multiple parameters for a specific application (Anzanello and Fogliatto, 2011). The basic power-law and exponential models are in the form of Equation 1 and Equation 2, respectively.

$$y = ax^b + c \qquad (1)$$

$$y = ae^{bx} + c \qquad (2)$$

In Equations 1 and 2, '*y*' indicates the performance obtained while producing the x^{th} unit while '*b*' indicates the learning rate with $b < 0$. Parameter '*a*' determines the starting point of the LC, which is the height at which the exponential curve intersects with the vertical axis, or where the power law crosses the line $x = 1$. Parameter '*c*' indicates the plateau of the curve, indicating the lowest feasible cycle time. This plateau arises due to limitations both in the environment and internal conditions of the worker.

2.3 Principles for Experiment Design on Learning

A designed experiment is searched for to validate the relationship between engineering changes and learning curves. The experiment requires the presence of an independent variable, the existence of a control group, and a random assignment of the treatment and control groups, to infer causality between a certain engineering change and a change in the MCT learning curve. Such an experiment setup is also referred to as a true experimental design (Campbell and Stanley, 1966).

The treatment group will be exposed to a change of the independent variable, in this case a parameter of the engineering change. In contrast, the control group is not exposed to a change in the independent variable. The third criterion, which is the random assignment of the experiment groups, partially ensures the internal validity of the experiment, which indicates the degree to which the results can be attributed to the independent variable and not by alternative, exogeneous variables (Bell et al., 2022). In practice, three different true experimental research designs can be identified: posttest-only control group, pretest-posttest control group and the Solomon four-group design (Campbell and Stanley, 1966). While the first two designs differ in the timing and number of the observations, the Solomon four-group design uses a second control group which is only tested at the end of the experiment.

In previous studies, experiments often take place in a physical space where participants are physically present and observed by a researcher. Recently, researchers have been utilizing virtual (online) experiments more often and have shown that data quality for interactive virtual experiments is adequate and reliable compared to laboratory studies (Arechar et al., 2018). Virtual experiments come with certain advantages such as accurate monitoring, cost saving and easy distribution which could facilitate a larger sample group. However, disadvantages compared to traditional physical experiments are also present such as lack of control, participant dropout, distraction, and the ability to ask questions during the experiment for feedback. Previous studies have shown that participant dropout is a particularly important challenge for virtual experiments and could jeopardize the internal validity of the experiment (Arechar et al., 2018; Zhou and Fishbach, 2016).

To mitigate the risk of dropout, gamification elements could be introduced to the experiment such as points, leader boards, rewards, or challenges. In this study setting this could be showing for example the speed of task completion of the test subjects, motivating them to focus on being as quick as possible. Studies show positive learning outcomes from gamification in terms of increasing motivation and engagement in the learning tasks and the enjoyment of them (Hamari et al., 2014). The implementation of gamification to a virtual experiment could be promising as it increases engagement and enjoyment among participants and thus likely decrease endogenous dropout and distraction from the task.

2.4 Product Complexity

Demand for high-performing and durable products is increasing, this results in most modern-era software-enabled, electro-mechanical products becoming more complex (Arthur, 1993; Frey et al., 2007). Increasing (product) complexity can play a significant role in the loss of manufacturing productivity following an engineering change (Jarratt et al., 2011). By quantifying the difference in product complexity between iterations of product, a company may be better able to predict the influence of this engineering change on their operations.

From an engineering perspective, product complexity lies within its connectivity and is often described as the difficulty to predict all behaviors and system properties of the interactions between several system elements (Anderson and Joglekar, 2012; Jarratt et al., 2011; Suh, 2005). The linkages and interconnections between system elements are often used as a measure for complexity (Johnson, 1995; Sosa et al., 2007). The interactions among system elements can lead to unexpected behaviors and patterns which can collectively be termed as emergent properties. These emergent properties can often not be inferred from the individual system elements and can lead to positive or negative consequences that impact the functionality of the product (Fisher, 2006).

Sinha (2014) developed a theoretical framework for the quantification of structural complexity of such products. The method is based on the mathematical property of matrix energy (Li et al., 2012). The generic form of the structural complexity metric can be seen in Equation 3.

$$C(\alpha, \beta, A) = C_1 + C_2 C_3 \quad (3)$$

'C' represents the structural complexity as a function of the complexity contributed the individual components C_1, complexity due to the individual interactions between the components C_2, and the complexity of the structure of interactions C_3. 'C_1' in Equation 4 is defined as the sum of the complexities of all individual components α_i. C_2 in Equation 5 is the sum of all pair-wise interaction complexities, where $\beta_{i,j,k}$ indicates the one-on-one interface of type k between components i and j. C_2 is also called the local effect. C_3 in Equation 6 is concerned with the effect of the system architecture and is also called the topological complexity. Here, E(A) resembles the matrix energy of the adjacency matrix A which is divided by the number of system elements n.

$$C_1 = \sum \alpha_i \quad (4)$$

$$C_2 = \sum \sum \sum \beta_{i,j,k} \quad (5)$$

$$C_3 = E(A) / n \quad (6)$$

This method for quantifying the structural complexity shows promising results. However, as the quantification of the singular components and interfaces are done by expert elicitation, the exact quantification of structural complexity remains challenging as this subjectivity could decrease the reliability of the metric.

2.5 Product Commonality

Engineering changes are necessary for companies to improve and innovate their products. The designs of most new products are refined versions of existing designs developed through incremental changes to certain components and their functions (Otto and Wood, 2001). As these engineering changes are often incremental, new improved products often share a large set of components with their predecessor. This overlap of components can be called product commonality.

This commonality in systems is vital when looked at the conceptual difference of complexity of a change and the change in complexity. For two systems, system A and System B, where System B is a technological successor of System A, the change in complexity from A to B will typically be reasonably small. The complexity of the change, however, is dependent on more than just the individual complexities of the two systems. Two radically different products could mathematically have the same complexity scores, e.g., small change in complexity. However, they may share little to no components or interfaces and their architecture might be completely different, which would result in a large difference in the complexity of the change. This latter type of complexity referred to here as the Delta complexity. This Delta complexity is mainly a factor of the level of product commonality, e.g., the addition or removal of components.

The study of Dooper et al. (2022) also mentions product commonality as a possible factor affecting the learning curve of MCT. They found that the starting point of an LC relative to the endpoint of its predecessor product appears to be related to the newness of the system after change e.g., the amount of overlap between the two systems. In their experiment they noticed that the uptick in MCT between consecutive LCs depends on how much of the new system is novel. Specifically, when a participant already had experience with a system that shared a large number of components, the uptick in MCT was observed to be smaller. The experiment was exploratory of nature and had only few participants; no statistical conclusions could be drawn regarding the hypothesized correlations.

3 Proposed Method for Quantifying Learning

To develop an experiment which validates the relationship between engineering changes that cause changes to the production process and manufacturing cycle time learning curves, the internal variable of engineering changes that affect the learning curve must be quantified. It is expected that both product complexity and product commonality have a significant impact on the learning curve. This is also supported by the preliminary findings of Dooper et al. (2022).

3.1 Quantification of Product Complexity

Equation 3 expresses that complexity is driven by the individual component complexity, the local effect, and the topological complexity. Both the individual component complexity and the local effect need expert elicitation to be quantified. We seek an experiment that circumvents the subjectivity of expert elicitation when modeling the complexity of a product before and after the change. For instance, it can be assumed that all elements and interfaces carry the same weight, also when new elements or interfaces are introduced with the change. The calculation of the topological complexity C_3 does not rely on expert opinion. In such a design experiment setting, a Design Structure Matrix (DSM) can be utilized to model and quantify the engineering change parameter (Sinha, 2014).

DSMs have been gaining popularity within several industries to model products and engineering processes (Eppinger and Browning, 2012). With a DSM the relationship between several components of a system is displayed in a compact, visual, and analytically advantageous matrix (Browning, 2001). In this matrix, each row and column correspond to a system component and each cell corresponds to an interface between two components. An off-diagonal mark in one of the cells signifies a dependency between the two components.

Equation 6 states that to quantify the topological complexity of a product, the matrix energy of the adjacency matrix A needs to be determined and divided by the number of components. The adjacency matrix A is equivalent to the DSM of the system (product) with all interfaces, e.g., off-diagonal marks, marked with 1 in the matrix and all other cells with 0. The matrix energy of adjacency matrix A can now be defined as the sum of the singular values of adjacency matrix A. In practice, when the matrix grows larger, the singular values and thus the matrix energy increases as well. With the DSM known before and after the engineering change, the difference in product complexity can be quantified using the topological complexity and assigning equal weights to the number of interfaces and individual components before and after the engineering change. In Figure 2 the DSMs of 2 fictional systems are displayed with their respective matrix energy. According to Equation 3 and the assumptions made earlier, the complexity score of the system in Figure 2b is higher compared to the system in Figure 2a.

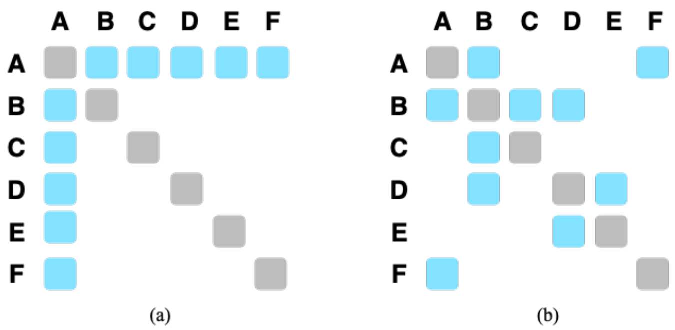

Figure 2. Example of 2 DSMs. DSM in Figure 2a has a matrix energy of 4.47. The DSM in Figure 2b has a matrix energy of 6.90. As both systems have an equal number of components and with the assumption of equivalent individual component complexity and interface complexity, the product complexity of the system in Figure 2b is higher.

3.2 Quantification of Product Commonality

DSMs are used to find the complexity difference between two systems. However, as mentioned in Section 2.5, a distinction must be made between the difference in complexity and the complexity of the delta (Delta complexity). Smaling and de Weck (2007) introduced the concept of a Delta DSM. The Delta DSM captures the number of new, removed, or redesigned components, new interfaces between components and changes in interfaces. The Delta DSM is constructed by taking the DSM of the original, pre-change condition, system and clearing all off-diagonal cells. Next, the new, removed or changed components and removed or changed interfaces are added to the matrix. An example of the construction of a Delta DSM is shown in Figure 3. Figure 3c shows the final Delta DSM indicating the changed interfaces with orange, a new interface with green, and a removed interface with red.

Figure 3. Construction of a Delta DSM. Figure 3a shows the pre-change condition of the system. Figure 3b shows the post-change condition of the system with changed component B2, added component E and 3 changed interfaces. Figure 3c shows the Delta DSM.

By calculating the complexity of the Delta DSM as proposed in Section 3.1, the Delta complexity can be determined. This Delta complexity could be hypothesized to relate to the steepness of the LC, as the search for the most efficient assembly strategy becomes more involved as this may be reliant on the level of product commonality with previous systems. The Delta complexity could also be hypothesized to relate to the amount of uptick at the start of a LC when a new product is introduced (Dooper et al., 2022)

4 Experiment Development

To validate the relationship between an independent variable of engineering change and the MCT learning curve, a robust experiment procedure must be adopted. As this study builds on the study of Dooper et al. (2022), a similar experiment approach is taken. In our proposed experiment, the participant needs to reassemble a virtual model of a bridge.

4.1 Design Requirements

We seek to develop an experiment which can validate the relationship between the engineering change and the MCT learning curve as described in Section 2.3. The following requirements have been identified:

DR1 The experiment needs to be scalable to a larger participant group ($n > 30$)
DR2 The experiment needs to follow a true experimental design, as discussed in Section 2.3
DR3 Models variants need to be able to differentiate in both product complexity and product commonality
DR4 Participants need to get direct feedback when an error is made in the assembly of the model variant
DR5 The experiment should have familiar behaviors for participants e.g. the difference in psychomotor effect among participants should be mitigated as much as possible
DR6 The assembly behavior of the participant needs to be logged in order to identify new assembly strategies which may point to learning.
DR7 The assembly time of the participant for each assembly iteration needs to be logged
DR8 Gamification elements need to be present in the experiment to mitigate dropout and participant distraction

DR1 and DR2 are both required for the validity of the experiment. DR3, DR6 and DR7 are in place to ensure that the correct parameters are measured which can create insights in the studied relationship. DR4 ensures that all assemblies to be congruent with each other and limits the possibility of alternative models being constructed by the participants and thus can be compared. In the experiment of Dooper et al. (2022), the observer was present in the same physical space as the participant and could give feedback when the assembly was not up to specification. As the proposed experiment will take place in a virtual environment, a direct feedback mechanism should be implemented in the environment. DR5 directly follows from insights gained by Dooper et al. (2022). In their study they found that after several iterations some participants showed new behaviors which decreased their assembly time that are not attributed to cognitive learning. The intended difficulty of this assembly task is such that any measured learning effect is mostly attributable to the cognitive aspect of learning, rather than the psychomotor component. As such, participants should increase their performance in the task by finding more efficient ways of ordering and clustering the assembly of different parts. Finally, DR8 aims to mitigate participant dropout, which could jeopardize the internal validity of the experiment as discussed in Section 2.3.

While this set of design requirements is not exhaustive, it does provide a solid basis on which the experiment can be developed.

4.2 Experiment Procedure

In the developed virtual experiment, the participants are asked to construct models of a bridge, Bridge Model A and Bridge Model B. These bridges consist of simple beams (rods) with a maximum length and joints on which the beams can attach. Bridge Model B has a higher complexity score compared to Bridge Model A. The models differ in product complexity, product commonality or both. Bridge Model B can be seen as a more complex model compared to Bridge Model A.

First, the participant needs to assemble 5 iterations of Bridge Model A. For each iteration, the assembly time and order of assembly are logged. After 5 iterations, the participant is asked to assemble a second model, Bridge Model B, again for 5 iterations. A second treatment group starts with 5 iterations of Bridge Model B before moving to Bridge Model A. Thus, for example, some treatment groups will move from a less complex model to a more complex model and vice versa.

The bridge assembly task is chosen as the models lend themselves well for changes in both product complexity as commonality without introducing different structural components. A limitation of Dooper et al. (2022), was that due to differences in individual components, their individual complexities and interfaces could differ which needs the assessment of the complexity of the individual components and interfaces as discussed in Section 2.4. Our idea is that this `simple' interactive bridge assembly game could provide for the experiment environment that enables to validate the hypothesized relationship between DSM-based quantified engineering change following Section 3 and parameters in typical learning models such as Equations 1 and 2. Subsequent validation experiments in the context of manufacturing can then build upon these first tests.

To be able to infer causality between the change of an independent variable such as product complexity and the MCT learning curve, a true experimental design needs to be adopted. In Section 2.3, several of these designs are mentioned. For this study, it is chosen to use an adapted version of the pre-test post-test control group design. For this experiment, a pre-test is necessary to establish a baseline of the assembly time of the first model. With the post-test the assembly times of the 5 iterations of the second model are recorded. The benefit of this design is that it can measure cognitive learning aspects, while minimizing the required resources compared to other designs such as the Solomon Four-Group Design which requires a far larger participant group especially as the experiment needs two different treatments. The research design is shown in Table 1. This design features 2 experimental groups. Experimental Group 1 is exposed to treatment X_1 which for example entails a switch from a simple model to a more complex model after 5 assembly iterations. Experimental Group 2 is exposed to treatment X_2, which will move from the more complex model to the simple model after 5 assembly iterations. The control group will assemble two models with equivalent complexity scores. This implies that every observation O_x will consist of a total of 5 measurements. With these results we aim to demonstrate that a change in product complexity, or the complexity of the change can be correlated to a significant change in the estimated parameters of the learning curve.

Table 1. Experiment Research Design

Experimental Group 1	R	O_1	X_1	O_2
Experimental Group 2	R	O_3	X_2	O_4
Control Group	R	O_5		O_6

4.3 Experiment Environment

The experiment will take place in a virtual setting, for this specific application an experiment environment needs to be developed. To satisfy Design Requirement 1, it is chosen to make the experiment run on a browser in an online environment. This allows for easy distribution among a larger sample group and a low threshold for participants to start as they do not need to download or install any additional software. After extensive online research and informal consults with experienced game developers it is chosen to use the Unity platform which is a game engine that functions cross-platform such as desktop, mobile, console and virtual reality. Through Unity, it is possible to use visual, node-based graphs to design final logic and create quick prototypes which enable an agile workflow. In Unity it is possible to develop both 2D and 3D environments, for this study’s purpose only a 2D environment is necessary.

As a first iteration, a prototype experiment environment has been created. This prototype creates familiarity with design methods within Unity and can be used to quickly test the assumption that cognitive learning is possible in such an experiment. This prototype features several critical experiment components such as anchor points where the bridge must be built in between, 2 different building materials, a 2D space world grid, a physics 2D engine to provide feedback to the participant and basic user interface (UI) elements such as a start and reset button. As this first prototype is designed for preliminary testing, no time or strategy logging features are implemented. Figure 4a, shows the prototype experiment environment where the participant is challenged to build a bridge between the two anchor points. In Figure 4b, the participant has built its bridge model. Finally, in Figure 4c, the bridge model is test whether it holds up to specification. This is done with the physics 2D engine using the stress on any of the singular beams, higher stress is indicated with a red shader.

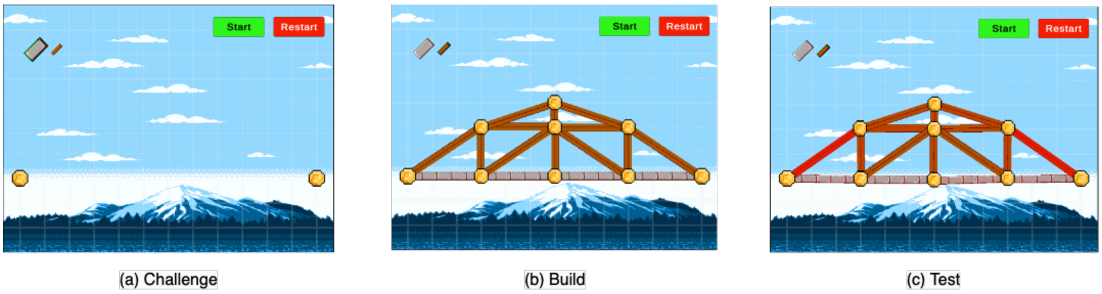

Figure 4. Prototype experiment environment with several experiment components. Figure 4a shows the initial environment from where the experiment starts and the participant is challenged to build a bridge. Figure 4b features the environment with a possible bridge model. Figure 4c shows the testing procedure which gives feedback to the participant by indicating the stress levels on the beams with a red shader. When the stress is too great, the bridge collapses.

To check whether this environment invokes the assumed participant behavior e.g., the participant can build a bridge model according to specification and improves its performance after each iteration by improving their strategy, an initial test with a single participant is conducted. Here the participant is asked to build a pre-designed bridge 5 consecutive times as fast but accurately as possible. The participant is not giving any other instructions or information about desired behaviors such as strategy changes and has no prior knowledge about the purpose of the study. The test results are shown in Table 2.

Table 2. Results initial test of prototype experiment

	Assembly time (s)	Error	Strategy Change
Iteration 1	34.90	Yes	-
Iteration 2	25.05	-	-
Iteration 3	16.81	-	Yes
Iteration 4	13.98	-	Yes
Iteration 5	11.50	-	Yes

From Table 2 it can be seen that after the first iteration, where an error was made, the participant continues to improve its assembly time. In the final 3 iterations the participant applies new strategies in the form of building order to further improve on their time, which is a sign of learning.

5 Conclusion & Future Research

This paper proposes a new method to validate the relationship between engineering changes and learning curves through a virtual experiment. Product complexity and product commonality are identified to be parameters of engineering changes which affect the MCT learning curve. A prototype experiment environment is developed in virtual space which allows the isolation of these parameters for accurate quantification using design structure matrix methods and thereby circumventing any expert elicitation requirements. The prototype experiment, although conducted on a small scale, has shown promising results that warrant further exploration.

The primary goal of this study was to establish a solid foundation for the experiment, and it has successfully laid the groundwork for future enhancements and advancements. While the prototype could not be distributed among a larger sample group, and thus provide statistically significant results, it provides valuable insights and serves as a proof of concept. The initial results indicate the potential effectiveness of such a virtual experiment in elucidating the relationship between engineering changes and the MCT learning curve.

This study provides several avenues for future research. First and foremost, it is vital that the prototype experiment environment is further developed into a full-fledged virtual experiment that can be distributed among a large sample group to gain any statistically significant results. The development of the experiment environment entails incorporating additional metrics, participant behavior logging features, refinement of the user interface and enhancing overall user experience. Second, it is essential to conduct a rigorous validation process to ensure the reliability and accuracy of the experiment's measurements and observations.

The potential implications of this research are significant. A validated virtual experiment that accurately captures the dynamics of engineering changes as a function of product complexity and product commonality, can serve as a valuable tool for engineering and project management professionals. It can aid in the decision-making processes, risk analysis, and resources allocation in manufacturing firms leading to improved project outcomes and increased efficiency.

References

Anderson, E.G., Joglekar, N.R., 2012. Mastering the Innovation Butterfly. pp. 1–23. https://doi.org/10.1007/978-1-4614-3131-2_1
Anzanello, M.J., Fogliatto, F.S., 2011. Learning curve models and applications: Literature review and research directions. Int J Ind Ergon 41, 573–583.
Arechar, A.A., Gächter, S., Molleman, L., 2018. Conducting interactive experiments online. Exp Econ 21, 99–131. https://doi.org/10.1007/s10683-017-9527-2
Argote, L., 2013. Organizational Learning, 2nd ed. Springer US, Boston, MA. https://doi.org/10.1007/978-1-4614-5251-5
Argote, L., Miron-Spektor, E., 2011. Organizational Learning: From Experience to Knowledge. Organization Science 22, 1123–1137. https://doi.org/10.1287/orsc.1100.0621
Arthur, W.B., 1993. Why Do Things Become More Complex? Sci Am 268, 144–144. https://doi.org/10.1038/scientificamerican0593-144
Barron, A.B., Hebets, E.A., Cleland, T.A., Fitzpatrick, C.L., Hauber, M.E., Stevens, J.R., 2015. Embracing multiple definitions of learning. Trends Neurosci 38, 405–407. https://doi.org/10.1016/j.tins.2015.04.008
Bell, E., Bryman, A., Harley, B., 2022. Business Research Methods, Sixth Edition. ed. Oxford University Press.
Browning, T.R., 2001. Applying the design structure matrix to system decomposition and integration problems: a review and new directions. IEEE Trans Eng Manag 48, 292–306.
Campbell, D.T., Stanley, J.C., 1966. Experimental and quasi-experimental designs for research. Rand McNally College, Chicago.
Dar-Ei, E.M., 2000. HUMAN LEARNING: From Learning Curves to Learning Organizations. Springer US, Boston, MA. https://doi.org/10.1007/978-1-4757-3113-2
De Houwer, J., Barnes-Holmes, D., Moors, A., 2013. What is learning? On the nature and merits of a functional definition of learning. Psychon Bull Rev 20, 631–642. https://doi.org/10.3758/s13423-013-0386-3
Dooper, D., Etman, P.L.F.P., Alblas, A.A., 2022. Quantifying the Impact of Product Changes on Manufacturing Performance, in: DS 121: Proceedings of the 24th International DSM Conference (DSM 2022), Eindhoven, The Netherlands, October, 11 - 13, 2022. The Design Society, pp. 38–47. https://doi.org/10.35199/dsm2022.05
Dutton, J.M., Thomas, A., 1984. Treating Progress Functions as a Managerial Opportunity. The Academy of Management Review 9, 235. https://doi.org/10.2307/258437
Eppinger, S.D., Browning, T.R., 2012. Design structure matrix methods and applications. MIT press.
Fiol, C.M., Lyles, M.A., 1985. Organizational Learning. The Academy of Management Review 10, 803. https://doi.org/10.2307/258048
Fisher, D.A., 2006. An emergent perspective on interoperation in systems of systems.
Frey, D., Palladino, J., Sullivan, J., Atherton, M., 2007. Part count and design of robust systems. Systems Engineering 10, 203–221. https://doi.org/10.1002/sys.20071
Hamari, J., Koivisto, J., Sarsa, H., 2014. Does Gamification Work? -- A Literature Review of Empirical Studies on Gamification, in: 2014 47th Hawaii International Conference on System Sciences. IEEE, pp. 3025–3034. https://doi.org/10.1109/HICSS.2014.377
Hedberg, B., 1981. How organizations learn and unlearn. Handbook of organizational design (1) 3–27.
Jaber, M.Y., Guiffrida, A.L., 2008. Learning curves for imperfect production processes with reworks and process restoration interruptions. Eur J Oper Res 189, 93–104. https://doi.org/10.1016/j.ejor.2007.05.024
Jarratt, T.A.W., Eckert, C.M., Caldwell, N.H.M., Clarkson, P.J., 2011. Engineering change: an overview and perspective on the literature. Res Eng Des 22, 103–124. https://doi.org/10.1007/s00163-010-0097-y
Johnson, J., 1995. The multidimensional networks of complex systems, in: Networks in Action. Springer, pp. 49–79.
Kim, D., 1998. The Link between Individual and Organizational Learning, in: The Strategic Management of Intellectual Capital. Elsevier, pp. 41–62. https://doi.org/10.1016/B978-0-7506-9850-4.50006-3
Kim, D.H., 1993. The link between individual and organizational learning. Sloan Manage Rev 35, 37–50.
Li, X., Shi, Y., Gutman, I., 2012. Graph energy. Springer Science & Business Media.
Lindemann, U., Maurer, M., Braun, T., 2009. Structural Complexity Management. Springer Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-87889-6
Mukherjee, A.S., Lapré, M.A., Van Wassenhove, L.N., 1998. Knowledge Driven Quality Improvement. Manage Sci 44, S35–S49. https://doi.org/10.1287/mnsc.44.11.S35
Otto, K., Wood, K., 2001. Product Design: Techniques in Reverse Engineering and New Product Development.
Salameh, M.K., Jaber, M.Y., 2000. Economic production quantity model for items with imperfect quality. Int J Prod Econ 64. https://doi.org/10.1016/S0925-5273(99)00044-4
Senge, P.M., 1998. The leader's new work: Building learning organizations., Leading organizations: Perspectives for a new era. Sage Publications, Inc, Thousand Oaks, CA, US.
Sinha, K., 2014. Structural complexity and its implications for design of cyber-physical systems. PhD Thesis, Massachusetts Institute of Technology.
Skinner, B.F., 1984. The evolution of behavior. J Exp Anal Behav 41, 217–221. https://doi.org/10.1901/jeab.1984.41-217
Smaling, R., Weck, O. de, 2007. Assessing risks and opportunities of technology infusion in system design. Systems Engineering 10, 1–25. https://doi.org/10.1002/sys.20061
Sosa, M.E., Eppinger, S.D., Rowles, C.M., 2007. A network approach to define modularity of components in complex products. J. Mech. Des. 129, 1118–1129.
Suh, N.P., 2005. Complexity: theory and applications. Oxford university press.
Wiendahl, H.-P., Scholtissek, P., 1994. Management and Control of Complexity in Manufacturing. CIRP Annals 43, 533–540. https://doi.org/10.1016/S0007-8506(07)60499-5
Wright, T.P., 1936. Factors Affecting the Cost of Airplanes. Journal of the Aeronautical Sciences 3, 122–128. https://doi.org/10.2514/8.155

Zhou, H., Fishbach, A., 2016. The pitfall of experimenting on the web: How unattended selective attrition leads to surprising (yet false) research conclusions. J Pers Soc Psychol 111, 493–504. https://doi.org/10.1037/pspa0000056