The impact of design debugging on new product development speed : the significance of improvisational and trial-and-error learning

The impact of design debugging on new product development speed: the significance of improvisational and trial-and-error learning

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Abstract

Investigating the antecedents of cycle time reduction is a continuing concern within new product development (NPD) research (Chen et al., 2010; Cankurtaran et al., 2013). A number of researchers have reported the effects of team learning on NPD speed (Dayan and Di Benedetto, 2008; Cankurtaran et al., 2013), while others relate learning to overall team performance (Magni et al., 2013). However, few studies have systematically researched the effects of improvisation and trial-and-error learning on NPD cycle time. The aim of this study is to shine new light on NPD learning and cycle time reduction through an examination of the effects of improvisation and trial-and-error. To that end, this study conceptualizes and tests the settings wherein improvisation and trial-and-error might contribute or hinder NPD cycle time reduction.

The authors develop hypothesis to investigate the effects of improvisation - and trial-and-error learning on NPD cycle time. Based on a review of the literature and in-depth interviews measures are defined to approximate improvisation and trial-and-error using secondary data from over 200 projects with absolute objective measures of cycle time. In addition, 1000s archival records of debugging incidents and engineering changes are used to approximate the impact of improvisation and trial-and-error. To estimate their impact on cycle time a learning curve model is developed (Argote, 2012) which offers an effective way of identifying the conditions that drive cycle time learning and performance (Wiersma, 2007). Based on this model the hypotheses are tested.

The findings suggest that improvisation and trial-and-error contribute to cycle time learning in the prototyping and pilot phases only, and that they hinder learning during later stages in the NPD process. These findings contribute to the extant literature by providing an important new organizational learning perspective on NPD speed. The study contributes to practice by relating firms' improvisation and trial-and-error practices to learning and speed performance.

Keywords: New Product Development, Learning curve, Cycle Time

Introduction

To date there are only a few studies that have investigated the NPD conditions across stages and the longitudinal consequences of initial project activity and performances on subsequent projects (Eling et al. 2013). The effect of conditions that change across stages is highlighted in several studies. Langerak and Hultink (2006) underline the impact of product innovativeness on NPD cycle time consequences. Eisenhardt and Tabrizi (1995) highlight the difference between a compression and experience based cycle time reduction strategy for different types of projects. Dröge et al. (2000) illustrate differences of cycle time driver effects in different phases of the NPD process. To contribute to the extant literature on NPD cycle time this research was set up with two primary aims: (1) to postulate a learning curve model to investigate longitudinal effects of NPD cycle time management; and (2) to determine the impact of learning on the cycle time effects of design process characteristics.

This study builds the argument that a substantial part of NPD cycle time driver ambiguity can be explained by the differences in learning by NPD teams. The fundamental premise of this study is that more experience leads to an increased understanding of the technology, user and field experience about the base line product design, and increased capability to cope with contingency changes. By investigating the impact of experience the objective is to scrutinize the ambiguity of the effects of learning on NPD cycle time reduction. One area that especially deserves attention is the management of the product design across the NPD stages as the literature does not show salient effects of design iteration on NPD cycle time (Cankurtaran, Langerak, and Griffin, 2013). For design debugging (i.e., testing) literature is quite consistent on the positive effects of cycle time reduction. However, the effects are not investigated by considering subsequent projects in a product line or the different stages of the NPD process.

The learning curve, defined as the function that describes the performance improvement when output or time is doubled (Argote, 2012), provides a rigorous conceptual lens that enables investigating longitudinal patterns in NPD cycle time management. Especially activities related to improvisational and trial-and-error based learning are postulated to contribute to performance (Miner at al., 2001). Improvisation in particular is a critical, yet neglected area of organizational learning (Crossan et al., 2005). Various scholars call for more systematic empirical research into both improvisation and learning (e.g., Baker et al., 2003; Crossan et al., 2005; Vendelø, 2009; Leybourne et al., 2014). This learning leads to improvements in the ability of teams to improvise, increases knowledge about previous trials, and thus enhances design iteration and design debugging skills. Accordingly, the more NPD design experience, the better the improvisational and trial-and-error activities, the better cycle time performance is ought to be. Anecdotal evidence suggests that being too late with design iteration and design debugging might negatively correlate with performance (Terwiesch and Xu, 2004; Terwiesch and Loch, 1999). In other words, the effects of design iteration and design debugging on NPD cycle time is expected to depend on the opportunity to learn within the NPD process.

Following this line of reasoning this study postulates to include the effect of experience in NPD cycle time research as a way to explain phasic differences of NPD projects. Specifically, the learning curve perspective allows us to test the influences of improvisational and trial-and-error based learning by specifying learning curves based on accumulated experience, design iteration, design debugging and NPD cycle time. These learning effects are further conceptualized by using the extant literature on trial-and-error and improvisational learning. By taking a learning curve perspective this is one of the few studies to undertake a longitudinal analysis of NPD cycle time reduction. This provides an angle for further research on NPD performance in general, and NPD cycle time in particular. Thus, the main contribution of this study is not only providing knowledge about the effects of design iteration and design debugging on NPD cycle time, but it also provides knowledge and methodology for longitudinal cycle time research.

Framework and Hypotheses

This research is anchored on the idea that cycle time reduction can be regarded as a two-sided coin. In some contexts cycle time reduction has advantages and while in other situations it better to spend more time (i.e., increase cycle time) to enhance learning. A learning curve model is developed to investigate the longitudinal effects of learning on NPD cycle time. Figure 1 provides the conceptual framework tested in this study. The remainder of this section is organized as follows. First, a conceptualization of the types of learning investigated in this study is provided. Then, an explanation of autonomous learning effects on cycle time is provided (H_1). Subsequently, the arguments for the mediating effects of improvisational and trial-and-error based learning on autonomous learning are explained (H_2-H_3). Specifically the learning curve model based on the effects of cumulative experience (CVOL) on NPD cycle time (CT), with mediated learning effects through design iteration (DI), and design debugging (DEB) is discussed. Finally, the hypotheses related to the effect of design iteration on design debugging is discussed (H_4).

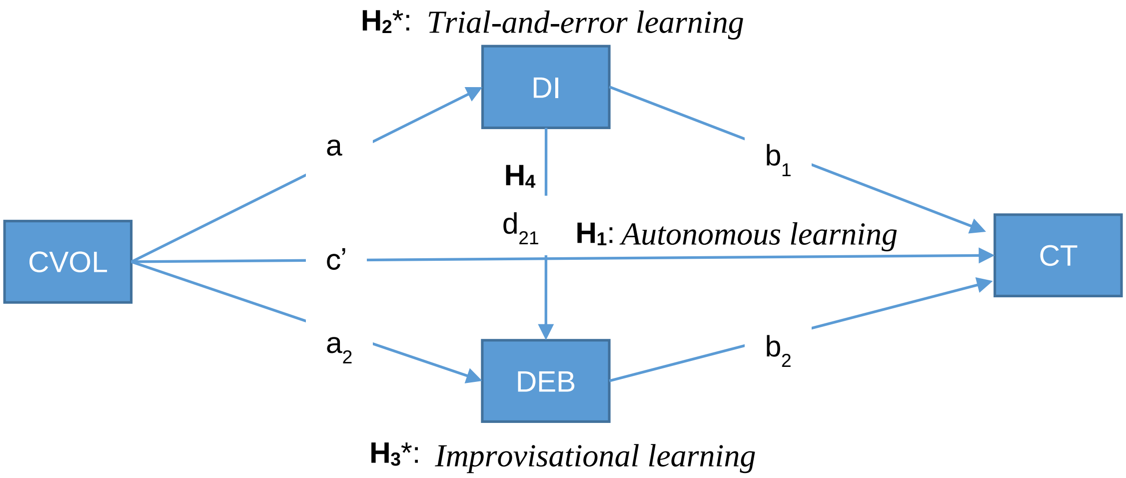

Figure 1 - Conceptual model (*refers to both the direct and mediated effect)

Three categories of learning: Autonomous, trial-and-error and improvisational

Organizational learning curve research is premised on the idea that accumulated experience creates knowledge that improves performance. Learning is generally measured using cumulative output volume or calendar time (Argote, 2012). In this study three types of learning are investigated: (1) autonomous learning; (2) trial-and-error learning; and (3) improvisational learning.

The first type of learning has been labeled "autonomous learning" (Dutton and Thomas, 1984), first-order learning (Adler and Clark, 1991) and learning-by-doing (Zoilo and Winter, 2002) in prior research. Autonomous learning emerges from the repetition of tasks that leads to experience in the execution of activities (Adler and Clark, 1991). Limited studies have related learning to cycle time while their obviously seems a connection. On the one hand, the opportunity to learn is hindered or supported by appropriate timing and sufficient duration (Berends and Antonacopoulou, 2014). Shorter time windows evoke improvisation (Vendelø, 2009) which in turn exasperates automatic learning (Miner at al., 2001). On the other hand, faster NPD allows for more development iterations and trial-and-errors, which also can stimulate learning (Eisenhardt and Tabrizi, 1995; Loch et al., 2006). This study relates autonomous learning to two types of learning that are expected to affect accelerated NPD: trial-and-error and improvisational learning.

The second type of learning investigated is “trial-and-error learning” (Miner at al., 2001). With trial-and-error learning problems are observed before or during NPD activity, but solved “on-line” by development. Although generic systematic knowledge can be the result, but it is often still localized and based on local decisions. The production of generalizable knowledge can be derived from comparing before and after effects (Miner at al., 2001). As such, unexpected outcomes may be noticed, but there is limited chance to relate expected or similar effects to the past. Trial-and-error learning emerges from activities (in this study related to design) that emerge from explicit managerial or operative intervention (Adler and Clark, 1991). Trial-and-error learning thus can be regarded as a special kind of induced learning (Dutton and Thomas 1984). In the literature this is also labelled as “deliberate learning” (Arthur and Huntly, 2005) and second order learning (Adler and Clark, 1991).

The third type of learning is related to improvisation. Improvisation is defined by the time convergence of an emerged problem or opportunity, and the design or production of a solution (Miner at al., 2001). It relates to a type of problem solving that takes place in experiential settings wherein product development problems are rapidly solved by hands-on improvisation and fire-fighting (Repenning, 2001). For trial-and-error learning the appearance of a problem and the search for a solution can diverge more with respect to time when compared to improvisation. Due to time convergence organizational behaviors are likely to have local value and are often tailored to specific settings where the problem arises. Therefore the related knowledge regularly is idiosyncratic in time and place (Miner at al., 2001). In the context of NPD this learning emerges from design debugs. Learning from design debugs is likely to take place in situations where output is limited (Terwiesch and Bohn, 2001) and where process improvements are postponed to volume production (Terwiesch and Xu, 2004).

Autonomous learning effects

Although many studies have been published on the antecedents of NPD speed, the literature shows ambiguity in the effects of some drivers (Cankurtaran, Langerak, and Griffin, 2013). Learning however is assumed to contribute to cycle time reduction albeit that prior research only investigated the effects at the individual project level through cross sectional research designs. If autonomous learning indeed explains a substantial part of variety in NPD cycle time this should also be captured using a learning curve approach. Although autonomous learning has been tested in the context of various types of induced learning (e.g., Adler and Clark, 1991), it has not been investigated in a cycle time setting. Therefore the hypothesis that will be tested in this study concerns the relationship between cumulative experience (i.e., autonomous learning) and NPD cycle time. Thus:

H_1: *Experience leads to significantly lower NPD cycle time (i.e. autonomous learning described in the form described by the learning curve formula).*

Our conceptualization in Figure 1 also allows comparing the effects of autonomous learning to other forms of learning by investigating the mediation paths. This is explained in the subsequent sections.

The mediating effect of trial-and-error and improvisational learning

Over two decades ago researchers already contemplated about the effects of the amount of design change (compared to previous generation) as a variable to explain variance in cycle time (Griffin, 1993). Other authors use other terms to refer to this phenomenon. Some authors talk about the frequency of prototyping and testing (Callahan and Moretton, 2001), while others refer to the number of redesign iterations before stabilization (Eisenhardt and Tabrizi, 1995). Some authors relate the process of building and testing a prototype in an NPD initiative with cycle time (Chen, 2010). In this study design iteration refers to the activities related to improving the product by changing the design. With design debugging this study refers to activities related to real-time solving of design related problems concerning qualification, testing, manufacturing, assembly, supply, and service.

In view of the effects of design iteration and design debugging on NPD cycle time and the impact of cumulative experience on NPD cycle time, one might logically expect a mediating role of trial-and-error and improvisational learning. Design iterations can be regarded as a specific source of learning (Miner at al., 2001). In an experimental NPD setting trial-and-error learning is the result of problem analysis and solution finding by engineers

(Macher and Mowery, 2003). The knowledge that is mined from design iteration is considered as a good proxy of trail-and-error learning for two reasons. First, design iterations are in many firms a well-established way to manage and communicate the explicitly knowledge about alternations to product designs. These often result from unexpected problems and evolving insights and are often labelled as engineering changes and solved "on-line" by specialized development teams (in line with Miner at al., 2001). Secondly, design iteration delivers possibilities for deliberate analysis of alternative problems and opportunities which can also lead to generic design knowledge (Miner at al., 2001). It is therefore postulated that design iteration follows an improvement pattern analogous to a learning curve. The more experience NPD teams have, the higher the quality of the products become, the less design iterations will happen. These arguments result in the following hypothesis related to experimental learning:

H_{2a}: Experience leads to significantly lower number of design iterations (i.e. trial and error learning described in the form described by the learning curve formula).

Although research has been reported about the impact of design iteration on NPD cycle time, it does not provide support for salient effects (Cankurtaran, Langerak, and Griffin, 2013). This research postulates that this ambiguous finding might relate to two alternative effects. On the one hand, the more design iteration activity, the more work, and thus the more cycle time required to finish the NPD project. On the other hand, more design iteration leads to a reduction of problems in the base-line design, less work in later design activity, and thus to a reduced NPD cycle time. In this study we postulate that along the entire NPD process the positive effects prevail. Therefore:

H_{2b}: Design iteration (i.e. trial and error learning) is positively associated with NPD cycle time

Next to the proposition about the direct effect, the intention is to investigate whether or not the relation between autonomous learning and NPD cycle time can be explained by mediated effects of trial-and-error learning. This is achieved by an analysis of the indirect effects of autonomous learning on NPD cycle time. Trial-and-error learning, which is defined by the relationship between cumulative volume and design iteration, is thus expected to contribute to cycle time reduction:

H_{2c}: Trial-and-error learning at least partially mediates the influence of autonomous learning on NPD cycle time

The final hypotheses explain the effects of improvisational learning effects. Improvisation learning is real time, requires creativity, and is a spontaneous immediate action in solving a problem or finding an opportunity (Magni et al., 2013). External time pressure, coupled with a lack of relevant prior experience may well be a common trigger for improvisation (Miner et al., 2001; Crossan et al., 2005). A typical example of improvisation in the context of NPD is design debugging, which is the enhancement of testability of a design by a quick fix or solution containment. In this study improvisation is defined as the convergence between design and execution (Baker et al., 2003; Moorman and Miner, 1998; Miner et al., 2001). It is assumed that the experience, labelled as improvisational, that emerges from the cumulative number of projects reduces the required design debugging activity in the learning curve form. Thus,

H_{3a}: Experience leads to significantly lower number of design debugs (i.e. improvisational learning described in the form described by the learning curve formula).

Yet, it is expected that this kind of learning is not a sinecure: when the design problem is solved the focus changes to continuation of the process which leads to limited automatic reflection. Terwiesch and Xu (2004) therefore suggest that unnecessary debugs must be postponed because they lead to unnecessary disruptions and have limited systematic learning. However, in the context of NPD the ability to rapidly react to unforeseen problems without delaying the project is especially important in highly innovative contexts. Moreover, it also can be a fruitful source for learning. Design debugging activity can be expressed as extra workload, while debugging might also have positive effects on cycle time performance in subsequent NPD activities.

H_{3b}: Design debugging (i.e. improvisational learning) is positively associated with NPD cycle time

Based on the above arguments, it is postulated that improvisational learning contributes to cycle time performance:

H_{3c}: Improvisational learning at least partially mediates the influence of autonomous learning on NPD cycle time

It is also postulated that design iteration leads to design debugging. Design iterations or design changes have all kind of disturbing effects on downstream NPD activities such as changes in prototype tools and changes in production tools (Terwiesch and Loch, 1999). They also lead to disturbances in processes (Terwiesch and Xu, 2004). Yet, these effects are not yet systematically tested. Therefore it is hypothesized that:

H_4: Design iteration is positively associated with design debugging.

Methodology

Empirical setting

The objective of this study was to develop a learning curve model to investigate longitudinal effects of NPD cycle time management. One of the decisions in the research design was to use objective data. Objective data was chosen over subjective data, because a meta study on NPD cycle time has shown that it provides stronger test results (Cankurtaran et al., 2013). This decision resulted in two initial requirements for selecting an empirical setting. First of all, it required us to select a company that provides the opportunity to collect highly detailed data. Secondly, it required us to conduct in-depth interviews and document studies in order to operationalize the theoretical concepts into proxies. The empirical setting of the study is an high-tech industrial machinery manufacturer in the Netherlands. The firm delivers lithography systems for the semiconductor industry and is world market leader. The development and production of these systems is very knowledge intensive and requires lots of investments in technology and people. Currently the firm has over 10.000 employees in more than 70 locations in 16 countries.

Next to these methodological arguments two theoretical selection criteria needed to be met. First of all, because the analysis aims to investigate learning effects of design activity in NPD context, it was important to select a setting that is characterized by technological turbulence and innovative firm climate (Swink, 2000; Langerak and Hultink, 2006). Secondly, our primary aim is testing the learning curve model in an empirical setting which required diverse cases. For the purpose of data analysis sufficient commonality is required for replication logic, but also sufficient diversity enables to search for diverse patterns (Eisenhardt, 1989). Case diversity allows finding conditions that shape learning (Wiersma, 2007). Although the study is limited to a single company, the research team was able to select embedded cases that show diversity technological turbulence and innovative climate. Based on this, two business lines were selected for in-depth analysis. These business lines are homogenous in terms of the organization of their main NPD process (e.g., the State Gate process). This allowed to build replication logic.

Variable measurement

The variables related to improvisation and trial-and-error were operationalized in three steps. First, interviews were held with several key informants that are involved in the research project. In these semi-structured meetings, the theoretical concepts related to learning curve were discussed, followed by questions and a discussion about key processes related to learning and cycle time improvements. The themes that emerged had a strong corroboration with the improvisation and trial-and-error concepts reported by Miner at al. (2001) and the design iteration and design debugging constructs. Next to these concepts measurement of cycle time was discussed.

In the second stage the research team inspected the company data archives for records that describe the properties of the design debugging and design iteration activity over time. Data on the NPD cycle time, number design debugs and design iterations formed the bases of our database. The analysis uses archival data of 740 NPD projects that were commercialized between 2005 and 2014. The analysis is based on a log transformation of the standard learning curve model: $CT = ct_o\ CVOL^{-b}$. The theoretical concepts, the operationalization and the empirical equivalents of the learning curve formula are presented in Table 1.

Table 1 - Operationalization of learning types

Concept	Operationalization	Equation
Autonomous learning	Cycle time (*CT*) is an exponential function of experience (*CVOL*)	$\ln CT_t = \delta_1 + \gamma_1 \ln CVOL_{t-1} + \varepsilon_{CT_t}$ (1)
Trial-and-error learning	Design iteration (*DI*) is an exponential function of experience (*CVOL*)	$\ln DI_t = i_1 + \alpha_1 \ln CVOL_{t-1} + \varepsilon_{DI_t}$ (2)
Improvisational learning	Design debugging (*DEB*) is an exponential function of experience (*CVOL*)	$\ln DEB_t = i_2 + \alpha_2 \ln CVOL_{t-1} + \varepsilon_{DEB_t}$ (3)

Serial mediated learning curve model

In the investigation how trial-and-error learning and improvisational learning relate to autonomous learning a serial multiple mediator model was chosen for several reasons. First of all, the research inquires the causal structure between the different types of learning. Thus, independency of mediators is rejected a priori. Therefore the study could not rely on a more common parallel mediator model that assumes independent mediators. A serial multiple mediator model not only allows to relax this assumption, it also enables to investigate these causal paths (Hayes, 2013, pp. 144). Following the estimation procedure of Hayes (2013), a cross-product of the coefficients approach is used to detect indirect effects. This approach provides a single test for the X–M–Y relations by multiplying coefficients of single paths. The generic formulation of a serial multiple mediator model with two moderators is:

$$\mathrm{M}_1 = i_{M_1} + d_1\mathrm{X} + \varepsilon_{M_1} \quad (4)$$
$$\mathrm{M}_2 = i_{M_2} + \alpha_2\mathrm{X} + d_{21}\mathrm{M}_1 + \varepsilon_{M_2} \quad (5)$$
$$\mathrm{Y} = i_Y + c'\mathrm{X} + b_1\mathrm{M}_1 + b_2\mathrm{M}_2 + \varepsilon_Y \quad (6)$$

In which X is modelled as affecting Y through four pathways with M_1 and M_2 as mediators. Using equations (1), (2) and (3) in (4), (5), and (6) results in:

$$\ln DI_t = i_{DI_t} + a_1 \ln CVOL_{t-1} + \varepsilon_{DI_t} \tag{7}$$
$$\ln DEB_t = i_{DEB_t} + a_2 \ln CVOL_{t-1} + d_{21} \ln DI_t + \varepsilon_{DEB_t} \tag{8}$$
$$\ln CT_t = i_{CT_t} + c' \ln CVOL_{t-1} + b_1 \ln DI_t + b_2 \ln DEB_t + \varepsilon_{CT_t} \tag{9}$$

Outcomes were assessed using a non-parametric bootstrapped multivariate approach to the cross-products of the coefficients proposed by Hayes (2013).

Results and analysis

The first column of Table 1 shows the effects of CVOL on DI, DEB, CT. The direct effect of experience (CVOL) on cycle time (CT) is statistically significant, which provides support for H_1 : c' = -0,0516, t(738) = 0,0001, P ≤ 0.01. The fourth and sixth columns of Table 2 show the effects of DI and DEB on resp. DEB and CT that will be further explained in subsequent sections.

Table 2 - Summary of results

("ln" signifies natural coefficients; standard errors in parenthesis; ** signifies P ≤ 0.01; * signifies P ≤ 0.02)

		ln CVOL		ln DI		ln DEB	R-sq	df	P
ln DI	a_1	-0,4207 **					0,2128	738	0,000
		(0,0298)							
ln DEB	a_2	-0,0305 *	d_{21}	0,3602 **			0,5500	737	0,000
		(0,0129)		(0,0141)					
ln CT	c'	-0,0516 **	b_1	0,2515 **	b_2	0,3480 **	0,6098	736	0,000
		(0,0131)		(0,0196)		(0,0372)			

Results related to the indirect effects

An inspection of Table 3 shows the results of the 95% bias-corrected bootstrap confidence intervals. The effects are all significant because the confidence intervals are different from zero. The first indirect effect is the specific effect experience on NPD cycle time through design iteration (ln CVOL → ln DI → ln CT), estimated as $a_1 b_1 = -0{,}4207(0{,}2515) = -0{,}1058$. Experience is significantly negatively related to design iteration (a_1), and design iteration was positively related to NPD cycle time (b_1). This result suggests that there is a significant trial-and-error learning effect and thus provides support for H_2. Yet this effect is dampened by the direct effect of design iteration on cycle time which was proposed in this study.

The second indirect effect is the specific indirect effect of experience on NPD cycle time through design iteration and design debugging (ln CVOL → ln DI → ln DEB → ln CT). This is estimated by $a_1 d_{21} b_2 = -0{,}4207(0{,}3602)0{,}3480 = -0{,}0527$. This suggests a significant learning effect. The path of b_2 confirms H_3 which postulates positive effects of design debugging on cycle time. In addition it can be concluded that design iteration significantly leads to design debugging which gives support for H_4. However, due to the learning effect between experience and design iteration, this leads to a limited learning effect.

The third specific indirect effect describes the effect of experience on NPD cycle time through design debugging (ln CVOL → ln DEB → ln CT), estimated by $a_2 b_2 = -0{,}0305\,(0{,}3480) = -0{,}0106$. The combined effect of the path suggests a very small, but significant, learning effect of experience on NPD cycle time through design debugging. This provides support for support for improvisational learning effect (H_6).

A comparison of the total effect with the indirect effects reveals that a substantial difference between the direct and total effects of CVOL on CT. The direct effect is -0,0516 (t = -3,9466, p < 0.01) and the total effects of CVOL on CT is -0,1692 with confidence intervals unequal to zero (-0,198 to -0,1392). This suggest that a big part of the variance of NPD cycle is explained by autonomous learning. However this effect is enhanced by trial-and-error learning and improvisation. Further inspection of Table 3 shows that design iteration provides the strongest learning effect followed by design debugging and autonomous learning from experience.

Table 3 Total and indirect effects

Learning type	Path	Effect	Boot $_{SE}$	Boot$_{LLCI}$	Boot$_{ULCI}$
Autonomous learning	ln CVOL → ln CT	-0,1692	0,0150	-0,198	-0,1392
Trial-and-error learning	ln CVOL → ln DI → ln CT	-0,1058	0,0132	-0,1348	-0,0816
Trial-and-error learning	ln CVOL → ln DI → ln DEB → ln CT	-0,0527	0,0073	-0,0692	-0,0399
Improvisational learning	ln CVOL → ln DEB → ln CT	-0,0106	0,0061	-0,0246	-0,0006

Discussion and conclusion

Although research has been reported about various design related drivers on NPD cycle time, it does not provide insight into the longitudinal effects of various drivers (Eling et al., 2013). The findings suggest that design iteration and design debugging have direct effects and longitudinal effects on cycle time. On the one hand improvisation and trial-and-error require cycle time, while on the other hand they increase learning. This research thus provides evidence that investigating longitudinal effects of NPD cycle time gives a profounder understanding of effects activities both short term and long term. Indeed, design iteration and design debugging lead to learning which is labelled as trail-and-error learning and improvisational learning. Yet, the results show that the direct effect of these activity have a delaying effect for individual NPD projects. Scholars can further investigate this trade-off while management can use this knowledge for their decision making.

The study has shown that learning requires people to spend time on improvisation and trial-and-error in order to achieve curved cycle time improvement. It is also show that NPD cycle time is especially reduced by trial-and-error learning. Nevertheless, also improvisational learning is observed. This is one of the first studies that addresses its importance in relation to NPD cycle time management. It can be concluded that the learning curve model provides a deeper understanding of cycle time management. The findings of this study thus provide plenty of new research possibilities on investigating structure and the effects of different types learning on NPD cycle time based on the learning curve model verified in this research.

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