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### Lean beyond waste

Roemeling, Oskar-Paul

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## **CHAPTER 2**

This chapter is currently under review at the *International Journal of Production Research* as: Roemeling, O.P., Land, M.J., Ahaus, C.T.B., Slomp, J, & Van Den Bijllaardt, W. (2016). Impact of Lean interventions on time buffer reduction in a hospital setting.

# **Impact of Lean interventions on time buffer reduction in a hospital setting**

## **2.1 INTRODUCTION**

This paper investigates the relationship between the long-term application of Lean principles and throughput time performance in a healthcare setting. We will focus on the process flow of a medical laboratory and study performance changes over six years. Healthcare is faced with increasing demands for excellent performance, the objective being to deliver increased quality while reducing costs. One of the approaches to performance improvement in healthcare is adopting a Lean philosophy (Burgess and Radnor, 2013; Clark, Silvester and Knowles, 2013). Holweg (2007) notes that the Lean philosophy has gained increasing attention since its popularization by Womack, Jones, and Roos in 1990. Over the years, Lean has been shown to be a facilitator of performance improvements in industry (Belekoukias, Garza-Reyes, and Kumar, 2014; Khanchanapong et al., 2014; Chavez et al., 2015). This increased attention for Lean in research, has resulted in a growing amount of scientific studies aimed at Lean applications in healthcare (Young and McClean, 2008; Poksinska, 2010; Holden, 2011). Despite the promising outcomes

(D'Angelo and Zarbo, 2007; Serrano et al., 2010), there is still a need for more empirical research focused on the application of Lean principles (Jasti and Kodali, 2015).

Current studies investigating Lean and performance in healthcare tend to focus on the short-term effects of Lean applications. This is problematic, since Marodin and Saurin (2013) report that the adoption of Lean in other sectors, such as health care, requires an effective performance of Lean in those sectors. According to Mazzocato et al. (2010), the research field has yet to reach maturity. Additionally, Poksinka (2010) comments that there is only limited evidence of the complete Lean philosophy being applied in healthcare. Rather, the concept is perceived as a set of tools and techniques aiming at process improvement. Based on the studies included in the review by Mazzocato et al. (2010), it seems that most reports of successful Lean implementations in healthcare focus on single event outcomes with Lean tools aimed at reducing waste.

While using tools that reduce waste can have a large impact on performance, it is not the only goal of the Lean approach. Targeting direct (or obvious) waste can be seen as the first step in Lean implementation, but one might also seek to reduce variability. The reduction of variability is of major importance, since variability has consequences for both patient service measures and healthcare costs (Salzarulo et al., 2011; Helm, AhmadBeygi and Van Oyen, 2011). In the longer term, the reduction of variability allows buffers to be minimized (Hopp and Spearman, 2004). In hospitals, there would particularly be an interest in reducing time buffers since these are perceived by patients as undesirable waiting time and may also increase healthcare costs due to longer stays in a hospital. Despite Lean having received attention for a number of years, the actual effects

of long-term adherence to the Lean philosophy are still unknown. Therefore, our main research question is: *how do Lean interventions influence time buffer performance over time?*

To investigate the relationship between Lean and time-buffer performance, we have conducted an in-depth longitudinal case study in a healthcare environment. For our study, we make use of data spanning a six-year period. We visualize Lean performance over time, and show the effects of adhering to Lean principles with the aid of statistical tests. In-depth interviews help identify the specific root causes that result in performance improvement. Our study is one of the first studies to investigate the effects of Lean on performance over such a lengthy period based on real-life data. We use triangulation, combining both quantitative and qualitative data, to strengthen the reliability of our results.

The structure of the paper is as follows. The first section introduces our theoretical framework. In the second section, the methodology is presented, and the case setting and chosen methods are outlined. Then, in our third section, covering our analysis and results, we analyze the changes in performance over time and investigate performance changes through in-depth interviews. The paper concludes with a discussion of our findings and the implications for future research. Ultimately, our study should help create a better understanding, both within academia and management, of the effects of prolonged adherence to Lean principles in a healthcare setting.

## **2.2 THEORETICAL BACKGROUND**

A substantial research base reports positive Lean effects in various healthcare settings (Ben-Tovim et al., 2007; Shah et al., 2008; Dickson et al., 2009). For example, Lean techniques have been

successfully applied to improve a histopathology department (Raab et al., 2008). In healthcare, studies commonly use various Lean definitions with a focus on the reduction of waste or the creation of value (e.g. Laing and Baumgartner, 2005; Fillingham, 2007). These definitions are then used as a theoretical basis for the approach adopted. Additionally, some applied studies (e.g. Raab et al., 2006; Grigg, Garrett and Miller, 2009) report on the usage of tools without providing a clear theoretical basis. In short, there seems to be no generally accepted Lean theory.

Lean is related to the Theory of Swift, Even Flow (TSEF) (Schmenner and Swink, 1998), which states: “the more swift and even the flow of materials through a process, the more productive that process is”. In essence, this means that lower throughput times increase flow and productivity, and thus performance (Devaraj, Terence and Kohli, 2013). Additionally, in a study by Fredendall et al. (2009) TSEF constructs are shown to affect flow speed and variance. Moreover, the TSEF emphasizes the role of reduced variability to allow for a more even flow, in accordance with the ‘Law of variability’ (Schmenner and Swink, 1998).

Shah and Ward (2007) underline the importance of variability within Lean with their definition of Lean as an integrated socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer, and internal variability. This reduction in variability is obtained through continuously improving processes (Radnor, Holweg and Waring, 2011). Still, despite variability clearly being an important aspect of Lean, healthcare-oriented studies often focus on direct waste. To go beyond the focus on waste, and help build a theoretical Lean

framework, we adopt the description of Lean by Hopp and Spearman (2004) and Hopp (2008).

From Hopp and Spearman's perspective, apart from reducing so-called 'direct' waste, reducing variability is of major importance. According to Hopp and Spearman (2004), when Toyota implemented Lean, they first switched the focus from inventory buffers, which 'hide' undesired variability, to capacity buffers. Then, by removing sources of variability through a continuous improvement process, both inventory and capacity buffers could be reduced. Ultimately this makes an organization Lean since the "production of goods or services is Lean if it is accomplished with minimal buffering costs" (Hopp 2008). Hopp (2008) distinguishes four phases of Lean implementation: (1) target direct waste, (2) exchange inventory for capacity buffers, (3) reduce variability, and (4) reduce capacity. Furthermore, one should cycle between phases three and four as part of continuous improvement initiatives. These phases can be considered development steps in becoming a mature Lean organization. Whilst testing the existence of these phases in practice is difficult, they do provide a frame of reference to argue that an organization with Lean experience should focus on more than just direct waste and show attention to buffers and variability.

While we expect inventory and capacity buffers to be present in healthcare organizations, we do not see inventory appearing in the core healthcare process of providing patient care (Jack and Power, 2004). Since patients are themselves transformed in the healthcare process, it is impossible to stock the transformed resource, the patients. When a queue of patients or patients' samples occurs, this should be seen, in terms of Hopp (2008), as the use of a time buffer (the customer requirement waits) and not as an inventory buffer. As

such, coping with variability in healthcare is mainly achieved through capacity and time buffers. This also means that we expect time buffers to fulfill the roles associated with inventory buffers, since both inventory and time buffers hide variability. Time buffers in healthcare most commonly relate to patients waiting for either diagnosis or treatment. Whilst capacity buffers relate to different capacity resources (such as staff or MRI machinery) waiting for jobs.

In adopting the Lean philosophy, we might expect healthcare organizations to initially focus on reducing direct waste (the first phase), which will be coupled with waste reduction tools such as 5S. Typical for direct waste is that it is visible or obvious. Contrary to variability, direct waste is not hidden by buffers. An example of direct waste is the time spent searching for medical equipment. Once healthcare organizations have been using Lean principles for some time and become more mature in their Lean approach, we might expect to see changes related to the later phases. We would therefore expect healthcare organizations in the later phases of Lean development to reduce variability to enable smaller time buffers, i.e. shorter customer waiting times.

Reduction in customer waiting times can be measured through decreases in throughput times for the process that the customer is waiting for. While we expect throughput time reductions to result from adhering to a Lean philosophy, the impact of adhering to the Lean philosophy in practice will only result from Lean interventions. A Lean intervention incorporates changes in work routines at a specific moment in time. These changes should relate to either direct waste, or to variability and related buffering requirements. Even when variability is a logical consequence of customer-specific operations, which certainly applies to healthcare settings, Lean approaches could

still seek to minimize the buffers needed to deal with this variability (Thürer et al., 2014). Especially for interventions in the mature phases of Lean adoption, we would expect a relationship between interventions and time buffer performance, i.e. decreased throughput times. In other words, the focus on Lean interventions allows us to investigate the relationship between *actual* Lean practices and their outcomes in terms of *actual* changes in performance. The method applied to investigate the relationship between Lean interventions and the time buffer is elaborated in the next section.

### **2.3 METHODOLOGY**

This research is a mixed-method longitudinal case study in which we combined both qualitative data resulting from interviews and quantitative data on throughput times. The case study approach is the preferred method when “the focus is on a contemporary phenomenon within some real-life context” (Yin, 2003). Here, the contemporary phenomenon comprises Lean interventions and their impacts on time buffers in healthcare. Further, we are able to study the phenomena over a lengthy period which makes the longitudinal case study approach particularly valuable (Voss, Tsikriktsis and Frohlich, 2002). The source of our quantitative data lies in the past, which means that we cannot have influenced the original data, thus avoiding the Hawthorne effect (e.g. Leonard and Masatu, 2006).

In order to investigate the influence of Lean interventions on throughput times, we required access to an organization that had a comprehensive Lean strategy and had been applying Lean principles over a prolonged period. In this study, we therefore focused on a hospital in the Netherlands that had been one of the first to adopt Lean approaches across the entire organization, and is still considered



a leader in Lean. Within this hospital, we focus on a medical laboratory that has seen hundreds of Lean-inspired improvements over the years. The extent of the Lean strategy in the laboratory is reflected in the richness of its practices and policies. Examples of Lean practices include employees applying tools such as 5S and participating in daily Lean meetings focused on continuous improvement. Policies include mandatory Lean training for new employees, and only hiring people that show an explicit willingness to work in a continuously improving environment.

The analysis of the data consisted of two main steps. First, and central to this study, is the analysis of quantitative data in the shape of throughput times for patient samples. Patient samples, such as blood or saliva, are processed in the laboratory and form highly homogenous groups with large numbers of flow units. This should enable statistically sound performance changes to be identified. Here, we view throughput time as an indicator of a time buffer. Second, we identify the causes of throughput time changes through a qualitative exploration. When a change in throughput time is identified, we consider whether this change can be attributed to Lean interventions.

The analysis steps will be discussed in detail after the case setting has been specified. First, we will further introduce the research setting, and then our attention switches to the data and the steps needed to enhance the data analysis possibilities. In the final part of this section, we elaborate on our statistical tests and the interview approach.

### Case Setting

The main task of the microbiology department consists of testing patient samples (e.g. urine) for the presence of bacterial infections,

and determining which antibiotics are best suited to curing these infections. When patient samples are delivered to the laboratory, the first step is to label these samples with an identifier to establish an order. Next, laboratory analysts inoculate the sample on petri dishes. After inoculation, the dishes are transferred to an incubator, which maintains a specific environment in which bacteria can flourish.

At pre-determined time intervals, dishes are inspected for bacterial growth. Samples that do not show the growth of clinically relevant bacteria after protocol times have passed are considered negative. Conversely, when samples do show clinically relevant bacteria, they are considered positive and undergo further testing. These later tests determine the type of bacteria, and their resistance to antibiotics. After either concluding that no bacteria growth is present, or after subsequent testing where the bacteria are identified, the initiator of the order receives confirmation from an analyst that the process is complete. The confirmation is the signal that no further processing is required for this order. After a final check by a microbiologist, the outcome is authorized, and the results become available to the applicant.

In our study, we focus on the laboratory process from the moment an order is created to when it is confirmed that the testing is complete. For our analysis, we divide the samples into two groups, positive and negative, since we anticipate seeing different and stronger effects of interventions in the positive group. Positive samples require additional handling and testing, and it is the waiting time in this period that can be influenced through interventions. In contrast, the negative samples have a larger part of their throughput times determined by medical protocols, i.e. the length of incubation, and should thus be less influenced by Lean interventions.

## Quantitative Data

In this research, the focus is on the quantitative performance first, and on the underlying causes later. Since hundreds of interventions took place, there would always be performance fluctuations that could indicate positive effects of preceding Lean interventions. However, the goal of this study is to identify Lean interventions that resulted in structural performance improvement. We are not interested in random or short-term performance variation. Our approach starts with objective performance data to reduce the chance of self-fulfilling prophecies. In other words, we avoid the risk of *wanting* to find performance changes, solely because there *has been* an intervention.

Alongside Lean interventions, external influences (such as legislation) can also influence realized throughput times. To counter the risk that such factors would confound our analysis, we followed the suggestion of Voss, Tsiriktsis, and Frohlich (2002) to use triangulation, and discussed our approach in meetings with laboratory specialists. The team of laboratory specialists did not identify any external factors that they thought might have influenced throughput times over the period of our study. Further, these meetings helped us in extracting the appropriate data from the database, helped in identifying appropriate data inclusion criteria, and provided us with our initial dataset as depicted in Table 2.1.

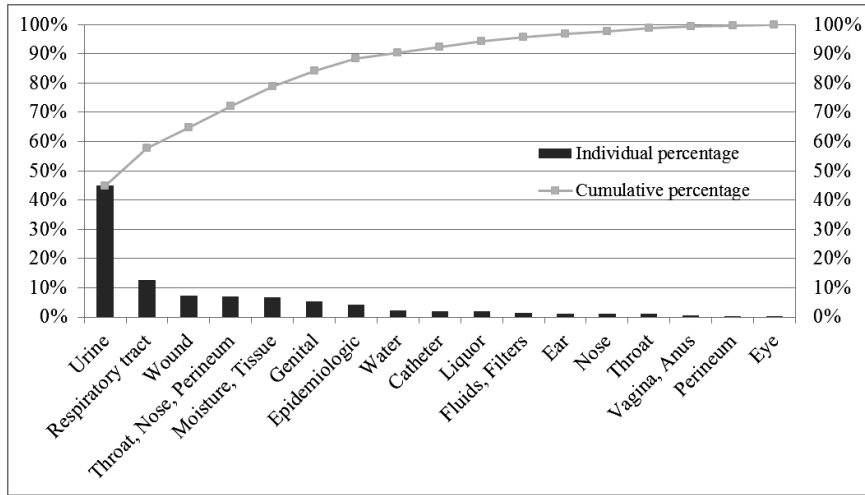
Our focus in the analysis should be on the bulk of the orders that appear to be reasonably homogenous in that they follow the same route. Therefore, samples that followed deviating routes were excluded from our analysis. For example, feces go through a special set of pre-processing steps because this sample type always contains

bacteria. Further, sample types that are not processed at least once a month were excluded. Although these would have little effect on our results (due to the low number) they could potentially cause disruptive effects on the mix corrections that will be introduced later.

**Table 2.1.** Data inclusion criteria and their effect.

Inclusion criteria / Procedural measure	Consequences for dataset		
	Records	Percentage	Sample types
Records for analysis after initial data cleaning (e.g. removal of deviating processes).	287,757	100	30
Removal of records with obvious errors (e.g. negative throughput times).	287,744	99.9	30
Removal of samples that are not processed at least once each month.	282,913	98.3	17
Removal of samples outside the upper and lower bounds put on throughput time.	260,323	90.5	17

Figure 2.1 shows a Pareto analysis for the sample types included in the dataset and indicates that the top six types account for almost ninety percent of the dataset.



**Figure 2.1.** Pareto analysis of the samples included in the dataset.

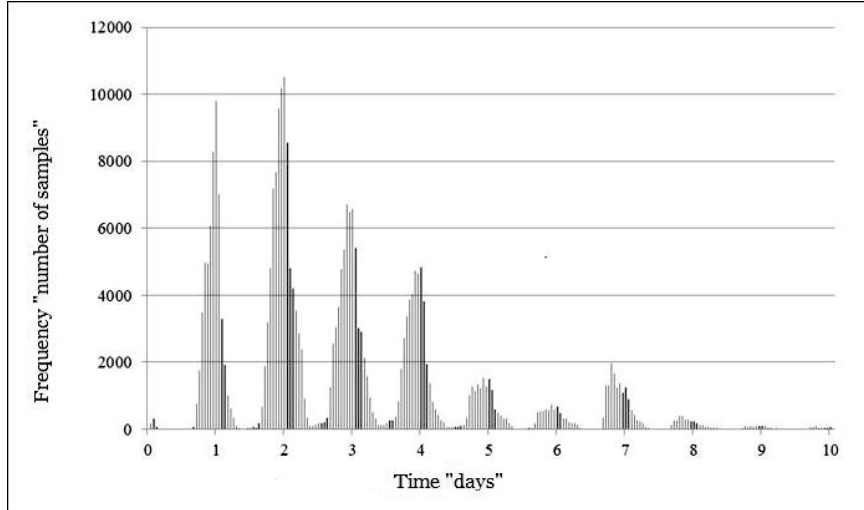
### Pattern Recognition

We adopted the moving average as our centrality measure to visualize patterns of throughput time performance. Averages were taken over a moving 28-day period to allow patterns in throughput times to be picked up. By using a multiple of seven days, we ensure equal numbers (here, four) of each day of the week are included in each average value. This avoids fluctuations caused by different throughput times for samples arriving on certain days of the week. Periods shorter than four weeks were investigated but the noise in the data was such that it became impractical to distinguish trends from normal fluctuations. With even longer periods, it became impossible to link trends to underlying Lean interventions because of the blurring of time, and because multiple interventions may underlie a single observed trend change.

To further guarantee robustness, we applied two operations in calculating moving averages:

- First, we focused on the key part of the throughput time distribution and removed outliers by only including throughput times between 16 hours (0.67 days) and 156 hours (6.5 days).
- We then corrected the averages for changes in the mix of samples processed over time. Since different samples require different incubation times, changes in the mix might cause changes in performance that are not related to interventions.

Figure 2.2 shows the distribution of individual throughput time observations and clarifies our choice in focus. Only samples with throughput times exceeding 16 hours were included since this is the normal minimum incubation period for specimens. The upper limit was imposed because the laboratory executes a ‘sample clean-up’ procedure after seven days in which unused, forgotten, or lost samples are discarded, and thus acquire a throughput time of approximately seven days or maybe longer. Including these measurements would distort our averages. In general, excluding the long right-hand tail of the distribution is useful, despite some of the extremely long throughput times reflecting lengthy incubation requirements rather than genuine outliers. However, small incidental changes in these long throughput times might heavily influence our averages and therefore we adopted a conservative approach and set our upper limit at 156 hours (6.5 days).



**Figure 2.2.** Distribution of throughput times across the samples.

Correction for mix changes was reasonably straightforward. The distinguished sample types are referred to by a combination of two indices  $i$  and  $j$ : with  $i$  indicating the type of sample (1 = urine, 2 = respiratory tract sample, etc.), and  $j$  indicating whether it was negative ( $j=0$ ) or positive ( $j=1$ ). Then the corrected average throughput time for a certain period  $t$  is calculated as:

$$T^t = \sum_i \sum_j f_{ij} \cdot T_{ij}^t \quad (1)$$

with  $f_{ij}$  being the fraction of all throughput time observations that were associated with samples of type  $(i,j)$  during the measurement period and  $T_{ij}^t$  being the average throughput time in period  $t$  for sample  $(i,j)$ . Note that the set of samples considered and the periods were chosen such that each period  $t$  contained at least one observation for each sample  $(i,j)$ .

Our initial approach to visualizing throughput time performance used the median as the centrality measure rather than the average.

The theory being that this would avoid the need to correct the data for outliers. However, as Figure 2.2 shows, the distribution of throughput times is multimodal. As the required incubation periods are multiples of 24 hours, the distributions of throughput times also show multiple modes at intervals of 24 hours. Consequently, while the median is normally a very robust centrality measure, it could lead to adverse effects with our multimodal dataset. That is, if the median was located between two modes, a small change in the data over time might result in the median value switching to either the preceding or the following mode. Conversely, if the median were to be in the middle of a mode, with many near-identical observations, even fairly major data changes would barely influence the median, which becomes ‘stuck in the middle’. So rather than displaying its normal robustness, the median could, here, be either extremely sensitive or insensitive to changes over time, and so we adopted the average as our centrality measure.

#### Statistical Analysis

Moving averages enabled us to visualize changes in performance over time. Where our visualization suggested the existence of distinct performance periods, we carried out additional testing. First, Kruskal-Wallis tests were executed for both positive and negative samples to investigate if there were statistically meaningful differences between the periods identified. When the differences were meaningful, we applied Student’s t-tests to further investigate these periods. For the statistical tests, we calculated weekly averages from the distinct performance periods to give a single (weekly) data point, since this enabled mix corrections to still be used. We took the corrected weekly averages for 33 consecutive weeks, from the first full week following February 1<sup>st</sup> in 2007, 2009, and 2011. This avoided any influence of



possible seasonal differences. We included only those sample types that were tested at least once each week. This left us with seven positive, and nine negative sample types to be included in the statistical tests. We applied the Bonferroni correction (Moore and McCabe, 2005) to address the problem that the significance level is influenced by conducting multiple tests, and set  $\alpha$  tightly at 0.005.

#### Qualitative Data Collection and Analysis

To reach a better understanding of the events that led to performance changes and to triangulate our quantitative findings, we conducted five semi-structured interviews. These specifically focused on those moments when changes in time buffer performance were observable. Since our interviews were aimed at recalling knowledge from previous years, we adopted the Event History Calendar (EHC) approach. Here, we provided each interviewee with time lines and important headlines from the news. The EHC is seen as a way to increase reliability because it enhances recall (Emans, 2002; Van der Vaart and Glasner, 2010; Glasner, Van Der Vaart and Belli, 2012).

The procedure for the interviews was as follows. One week prior to the interview, an interviewee received an e-mail containing a reminder of the scheduled interview plus the EHC materials. These materials consisted of a timeline with selected headlines related to major events from the years 2007 to 2012. More detailed timelines with a higher density of events were provided for 2008 and for 2010, since the preceding data analysis had shown the largest performance changes in these years. In the e-mail, interviewees were asked to think about the events listed and recall events from their own experiences that had happened in these periods. The first four interview questions related to broad knowledge of the Lean philosophy and the interviewee's

background. Then the interviewee was asked to spend ten minutes on the EHC task. This involved studying the EHC materials and adding meaningful personal events to the timelines. When this EHC task was complete, the interview continued with ten questions related to time buffer performance changes. The interview questions are available in the online supplement.

To reach a better understanding of the events that led to performance changes and to triangulate our quantitative findings, we conducted semi-structured interviews. The respondents were selected on the basis that they had been working in the laboratory sufficiently long to have witnessed all the events, had a thorough understanding of the laboratory process, had experience with Lean, and would be informed about most of the Lean interventions. These criteria resulted in the identification of five interviewees:

- a chief analyst, who was head of the bacteriology department and involved in most of the department's Lean interventions;
- a database expert, professionally trained as an analyst and facilitating all the database requests for the laboratory;
- a Lean expert, professionally trained as an analyst and involved in Lean interventions throughout the hospital;
- two physician microbiologists who were part of the laboratory's management;

The respondents were all male, and had been working for the laboratory for 20.6 years on average (minimum 11, maximum 26). All the interviewees had received substantial training on the Lean philosophy, and their experience with Lean varied from four to eight years, with 6.4 years as the average. When asked to compare their Lean knowledge with people in similar positions, all considered they

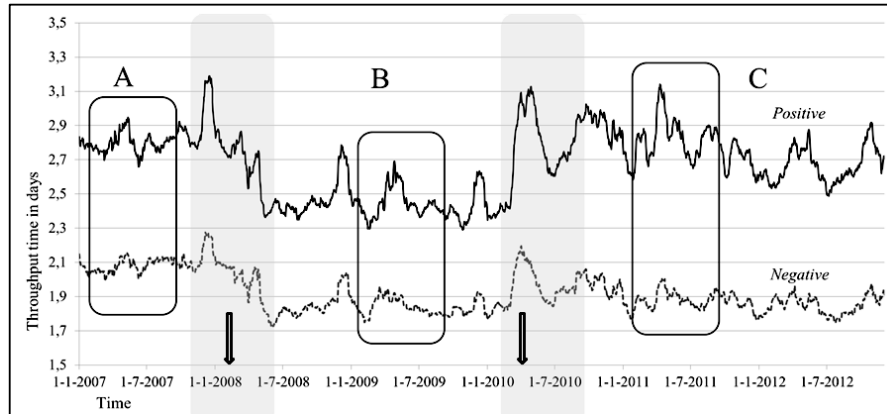
had above-average knowledge. All the interviewees had an expert understanding of the laboratory processes. We refer to the respondents as interviewees A – E, with these labels randomly assigned to protect the respondents' identities.

The first step in analyzing the recordings of the interviews was to transcribe them. Then, following the advice of Miles and Huberman (1994), the interview questions and related answers were positioned in a matrix. In the matrix table, answers are listed by interviewee, which allows for a quick comparison between the answers of the different interviewees. Effectively, based upon the constructed table, we assess whether our experts shared views on the causes of changes in throughput performance. If the same cause was identified by multiple respondents, we saw that as corroboration for the event having caused a performance change.

## **2.4 ANALYSIS AND RESULTS**

### Quantitative Data: Patterns and Statistics

Figure 2.3 presents the 28-day moving average of throughput times over the entire studied period, and we distinguish between positive and negative samples.



**Figure 2.3.** Moving average of throughput times: performance trend.

From Figure 2.3, it is immediately clear that, even after eliminating irregularities and applying smoothing techniques, there is still quite some variability in the performance. However, two major shifts in throughput time performance are clearly present. The first is in early 2008 when throughput times started to become noticeably shorter than in the previous period. A second change occurs in early 2010, when throughput times increased sharply. As such, the six-year period studied can be typified by three distinct periods in terms of throughput time performance which we have labeled A, B, and C. Period A, is the year 2007. The second period, B, lasts from the middle of 2008 through to early 2010. The third period, C, starts in the middle of 2010 and continues at least to the end of our analysis in late 2012. Rather than step changes, there seems to be transient periods, which we have shaded in Figure 2.3.

To investigate these periods, we compare the means of three equal-length time periods, well away from the transient periods, within periods A, B, and C. The tested periods are indicated by the rectangles

in Figure 2.3. Table 2.2 shows the results of the Kruskal-Wallis tests carried out for both positive and negative samples.

**Table 2.2.** Results of the Kruskal-Wallis test for both positive and negative samples.

<b>Kruskal-Wallis Test</b>	<b>Positive samples</b>	<b>Negative samples</b>
Null hypothesis	The distribution of weekly average throughput times is the same in the three distinguished time periods A, B, C.	
Significance	0.000**	0.000**
Result	Null hypothesis rejected	Null hypothesis rejected

\*\*sig. level <0.005

Based on the Kruskal-Wallis test results, we conclude that the specific periods can indeed be typified by different distributions of throughput times and, therefore, additional tests are justifiable. To further investigate the differences between the periods we carried out Student's t-tests on the means. The results of these tests are provided in Tables 2.3 and 2.4 for positive and negative samples respectively.

**Table 2.3.** Results of the Student's t-test for positive samples.

<b>Period</b>	<b>Mean</b>	<b>DF</b>	<b>T</b>	<b>Sig.*</b>
A vs. B	3.040 (A) 2.653 (B)	64	10.621	0.000**
B vs. C	2.653 (B) 3.040 (C)	64	-7.249	0.000**

\*two tailed, \*\*sig. level <0.005

**Table 2.4.** Results of the Student's t-test for negative samples.

<b>Period</b>	<b>Mean</b>	<b>DF</b>	<b>T</b>	<b>Sig.*</b>
A vs. B	2.371 (A) 2.112 (B)	64	11.956	0.000**
B vs. C	2.112 (B) 2.133 (C)	64	-0.923	0.359

\*two tailed, \*\*sig. level <0.005

The t-test results for the positive samples show that the mean throughput times in our chosen period are significantly higher in 2007 (period A, mean 3.040 days) and 2011 (period C, mean 3.040 days) than in 2009 (period B, mean 2.653 days). The t-test results for the negative samples show that the mean throughput time was significantly lower in our selected period of 2009 (period B, mean 2.112) than in 2007 (period A, mean 2.371). However, unlike with the positive samples, there was no statistically significant change in throughput times after 2009 for negative samples.

The mix corrections introduced earlier control for fluctuations in the types of samples. Table 2.5 shows that changes in throughput times also cannot be attributed to changes in total requirements. The total number of samples in period B is higher than that in period A, whilst throughput times were shorter in period B. In period C, the number of positive samples hardly increased relative to period B, but throughput times increased significantly.

**Table 2.5.** Distribution of positive and negative samples of the years.

	<b>2007</b>	<b>2008</b>	<b>2009</b>	<b>2010</b>	<b>2011</b>	<b>2012</b>
Period	<b>A</b>		<b>B</b>		<b>C</b>	
Positive	20,098	21,875	22,614	22,290	22,919	20,668
Negative	23,880	26,264	25,393	27,182	26,119	23,639
Total	43,978	48,139	48,007	49,472	49,038	44,307

Based on these quantitative results, we conclude that throughput times in the laboratory had indeed changed between various periods, and that these changes have been different for positive and for negative samples. Hence, we assume that Lean interventions could provide a feasible explanation.

#### Qualitative Data Analysis and Results: Explanations

In order to explain the quantitatively identified changes in performance, we continued our research with a qualitative exploration of possible causes. Each of the interviewed professionals were asked to list what they thought to be the three most important changes based on them having significantly impacted throughput time performance over the past six years. The interviewees provided their responses, tabulated in Table 2.6, before being confronted with the visualized performance trend.

**Table 2.6.** Interviewee top three events.

<b>Respondent</b>	<b>Change event</b>		
A	New working method	New machinery	Overhaul of the lab*
B	New working method	New machinery	Overhaul of the lab*
C	New working method	New machinery	Attention to Lean
D	Changes in staffing	New machinery	Overhaul of the lab*
E	Lean workshop 2007**	Consultants from X	Consultants from Y

\*Rebuild was coupled with new working method.

\*\*First time the laboratory heard about Lean.

Three of the five respondents referred to a change in the working method in the bacteriology department, as a consequence of their Lean program, that they thought would have caused changes in throughput time performance. This new working approach was facilitated by a rebuild/overhaul of the laboratory, which perhaps explains why several interviewees felt this was an important change event.

Further, four of the five respondents listed the introduction of a new machine for the incubation process as an event that influenced throughput times. The laboratory professionals considered the introduction of this new machine as a Lean intervention. The machine led to a ‘one-piece-flow’ working methodology, and a focus on flow is generally considered part of the Lean philosophy (Spear and Bowen, 1999; Shah and Ward, 2007).

The answers provided by respondent E offered a different perspective to those of the other respondents, and focused more on social events and individuals. However, when respondent E was



confronted with the specific performance changes discussed in the following paragraphs, his responses related to the causes commonly identified by the other interviewees.

#### Performance improvement 2008

First, we sought to explain the sudden improvement in throughput time performance in early 2008. The laboratory professionals thought that a new way of working, and which was in line with Lean principles, to be the most plausible explanation for the improvements. This new way of working was inspired by the one-piece-flow approach.

Interviewee A: *“I believe that it (the performance change) is due to the change in work methodology; we switched from working based on the patient’s name towards a station-based approach”* and interviewee B: *“One of the events that should be considered when addressing the bacteriology department is adopting a different work method”* and interviewee C *“Well, that just means a different way of working, a new division of labor amongst our people”*.

The next question aimed to investigate what actually changed due to the introduction of the new working method, in order to determine whether the observed performance change could causally be attributed to it. The laboratory had stopped the preprocessing steps that consisted of creating batches based on a patient’s family name and hospital department. As such, the new working method meant that the laboratory had switched from needless grouping (or batching) to a process that was more in line with the ‘one-piece-flow’ principle. In essence, they had started to focus on introducing flow into the process and avoided the time needed for batching.

Interviewee B: *“Process-focused work - so we have our inserts, then the next step and so on; and we physically put these steps in*

*their sequential order in the laboratory. So samples go from the front to the back of our laboratory, and at this point the process is finished.”*

In the original setup, a laboratory employee would perform all the processing steps for an order, for which they carried full responsibility. The change in work methodology meant laboratory employees became responsible for a specific part of the process and received standardized work quantities. In terms of the Lean philosophy, this could be seen as the introduction of mixed modelling and Heijunka (production leveling).

Interviewee B: *“There was no understanding (in the previous situation) as to what kind of quantities of work there were for everyone.”* Interviewee C *“so, eventually, we stopped separating samples, which meant people got allocated a standard number of petri dishes.”* Interviewee D: *“Based on a Lean approach, we just took everything (all types of samples, patients, departments) together.”* This may explain another element of the reduced waiting times. Previously, some analysts might have a low ‘utilization’ while others were highly utilized, causing samples to be delayed.

Based on the explanations of the laboratory employees, it is clear that the previous batching (referred to as separation by the laboratory employees) cost unnecessary time and effort whilst failing to add value to the process. In applying their new Lean knowledge, they considered the creation of batches to be a form of direct waste.

Interviewee E: *“In the early days you had a separation of samples. In other words, we separated urines, we separated the IC (Intensive Care) which, together, costs a lot of energy. It was just over processing, the separation of samples and distributing them to different servers.”*

This division existed because it was the way they had always worked and it was considered to be the “*state of the art*” (interviewee E). However, through their Lean knowledge, they were able to boost performance by reducing direct waste and by balancing the workloads of the servers. In essence, the laboratory started to make better use of its available capacity, which resulted in improved throughput time performance. Interestingly, they did not consider the effects these steps could have on waiting times. Rather, they focused on the time it took to create the batches, which they saw as excessive processing steps.

Both the positive and negative samples were influenced by these changes, albeit to varying degrees. The differences in throughput times between the positive and negative samples stem from the fact that positive samples require more employee input and handling. Negative samples are only checked for bacteria growth, whereas positive samples then require additional testing.

Interviewee A: *“It is just more laborious, you have to take additional steps, have things wait an additional day.”* and interviewee B *“Positive samples just require more time, you’ll be working for three days on a positive sample whilst negative samples are gone after one day.”*

#### Performance after 2010

Apart from the performance improvement in 2008, Figure 2.3 also indicates a change in performance in 2010. Suddenly, positive samples seemed to require longer to process whilst negative samples’ throughput times remained constant. According to our laboratory professionals, the cause for this decrease in performance was linked to the introduction of a new machine (NM) for the incubation process.

The laboratory viewed the introduction of the NM as part of their Lean initiative, or a Lean intervention, as the equipment required (and facilitated) working in a ‘one-piece-flow’ manner.

Interviewee E: *“Easy, (that’s because of the) NM.”* Interviewee C: *“That’s solely the implementation of the system related to the NM.”* Interviewee B: *“This should be the NM. Yes, that really was a major process change, a very different way of working.”*

In order to clarify the changes due to the NM, a short explanation of these changes is provided next. Before the implementation of the NM, the laboratory employees physically inspected the petri dishes for bacteria. The employees were also responsible for transporting the petri dishes to and from the various incubators. The NM changed this way of working by providing the employees with a conveyor-belt system that transported the inoculated petri dishes to an incubator that had the ability to deliver high quality photographs. These images of the petri dishes could then be studied on a computer screen. If it was decided that a sample required additional testing, the NM will return the petri dish to the employee through the conveyor system. In principle, the way the NM is setup requires one and a half FTE fewer personnel (although there have been no resulting layoffs). At first glance, the introduction of the NM does not seem to pose major issues. However, there was little doubt amongst our professionals that the increased throughput time for positive samples was linked to the introduction of the new NM. Why then did the introduction of the NM lead to a worse throughput time performance? Two main reasons were advanced as to why the NM slowed the process. First, the laboratory employees had to learn how to work with the new equipment.

Interviewee B: *“You have to get used to it, it’s a totally different way of working with images (instead of physically holding the petri*

dishes). *You need explanations (on the working of the NM) and ask questions, and that does mean longer throughput times.*” Interviewee C: *“Then you end up with an entire period where you have around twenty analysts having to learn how to work with this particular system.”*

During the early phases, the machine also suffered some, what can best be described as, teething problems. Combined with the lack of knowledge amongst the employees this partly explains the increased throughput times. However, after a certain period of time, one would expect these issues to be resolved, and performance to return to the original level. Yet, this was not the case. As such, the learning process cannot be the reason for the prolonged decrease in throughput time performance. The laboratory professionals raised another issue linked with the NM. The NM has to perform several tasks, i.e. incubate samples, take photographs of the samples, and deliver petri dishes to the employees for further processing. However, the NM is only capable of performing one of these tasks at a time. Furthermore, certain tasks have priority over other tasks.

Interviewee A: *“My belief is that the NM was not properly set up and tuned, so you had to wait a long time for your (petri) dishes.”*

The NM re-introduced a batching approach, but now based on prioritizing tasks. For example, photographing samples is always considered more important than delivering petri dishes. Thus, photographic tasks were batched and, as a consequence, the machine would be creating an inventory of pictures that would not necessarily be urgently required.

Interviewee C: *“If you consider the prioritization, making a photograph has a higher priority than delivering a petri dish. So, we would have an analyst requesting dishes to process. However,*

*because the NM was still busy with photographing dishes, requests for dishes would be overruled.”*

In practice, this meant that laboratory employees had to wait, sometimes for up to 18 hours, before they obtained a required petri dish. One aspect of this was that the NM, as soon as it became operational, was operating close to its maximum capacity, which caused even more delays. Essentially, the laboratory had created a highly utilized resource, which is against Lean principles.

Interviewee B: *“It is slow, yes, the retrieval of dishes. They are improving it now, but it works slowly.”* Interviewee C: *“Additionally, whilst we were working with the system, we started to notice that we were right at the peak of its possible capacity.”*

The clear difference between the time involved in testing positive and negative samples when the NM was introduced stem from the explanation given earlier: that positive samples require further employee handling. Given that the NM takes longer to deliver the petri dishes for further testing, we end up with a combined effect: positive samples inherently take more time to process, but they now also have increased waiting times because of the NM. Negative samples are not delayed further by the NM because these do not require further testing once the photograph has been taken.

Interviewee C: *“The negative samples are not returned. They merely take their turns in the system. When they are finished (the protocol time has passed), they are discarded.”*

From a Lean adoption perspective, the machine could be considered as an advanced Lean intervention. The machine increases the capacity buffer, and it introduces task standardization, which reduces the processing variability that would normally stem from having different operators. However, these advantages did not result

in decreased throughput times for either positive or negative samples. During the interviews, laboratory employees identified the initial learning process as the main reason for the decrease in throughput time performance. However, learning to operate a new machine should not take years, and one would have expected to see the effects of learning on both negative and positive samples. A more plausible explanation for the reduced performance relates to the time the new machine takes to deliver petri dishes for further processing, and the fact that it has become a highly utilized resource.

We were unable to pinpoint the exact timing of the interventions preceding the changes in throughput times. The arrows in Figure 2.3 indicate the approximate timing of the ‘new working method’ and ‘new machinery’ Lean interventions that were revealed in the interviews as ‘reasons’ for the changes in throughput time performance.

## **2.5 DISCUSSION**

In this study, we set out to explore how Lean interventions influence time buffer performance over time. Based on the theories discussed, we would expect interventions that reduce variability to allow successive time buffer reductions, and we would expect to see such interventions in mature Lean organizations. However, whilst there have been numerous interventions in the studied case, which had been selected largely on the basis of its maturity, most of these interventions had either no effect on throughput time performance, or the effects were lost in the ‘noise’ of throughput time variability. Only two ‘Lean’ interventions have had effects that were sufficiently substantial to be statistically significant.

Our results indicate that the early changes in work methodology improved throughput times for both positive and negative samples.

The batching applied previously can be seen as artificial variability in the terms of Litvak and Long (2000). Interestingly, this intervention was never explicitly intended to reduce time buffers and, further, addressing buffers and variability did not appear to be a conscious part of the laboratory's Lean approach. Furthermore, these positive results were obtained early in the laboratory's Lean transition whereas, based on the model by Hopp and Spearman (2004) of the different Lean phases, we would expect a focus on variability to only appear later, once an organization achieves Lean maturity. In that sense, the case investigated challenges conventional wisdom regarding progression towards Lean maturity.

Continuous process improvement plays a central role in the laboratory, and in the Lean literature (Radnor, Holweg and Waring, 2011). However, our results did not exhibit a pattern of continuously improving throughput times. One might have expected a declining pattern to be evident over time in Figure 2.3. Yet, after the first significant decrease, performance remains stable for negative samples, and even deteriorates for positive samples, after 2010. Whilst the continuous improvement of processes is often considered a hallmark of the Lean approach (e.g. Chen, Li and Shady, 2010), and our case organization does implement improvements on a continuous basis, these do not clearly result in continuously improving performance.

The worsening performance in the laboratory in the later years of our research period is hard to explain if one relies on the common idea that Lean leads to improved performance (Womack, Jones and Roos, 1990). It could be questioned whether the adoption of the new machinery should be considered a Lean intervention. However, the mere fact that a specific intervention does not result in improved performance is not sufficient to categorize it as 'not' Lean, since such



reasoning would result in a situation where only interventions that have positive outcomes are considered Lean. In essence, we have to accept that applying and adopting Lean ideas might, in some situations, have an unintended negative impact.

Given the laboratory's focus on continuous improvement, we would have expected the worsening performance to have been picked up, and effort put into restoring the initial gains. However, we should not overlook the fact that this laboratory is a pioneer, both with the adoption of Lean and in the use of the new machine. Additionally, until this study, the laboratory had never seen their actual throughput performance laid out this clearly. Whilst they were aware that positive samples had longer throughput times, they had no structured methodology that could show them how much their performance had deteriorated. Moreover, as reflected in our initial methodical struggles, visualizing performance is not that straightforward. Besides not being able to use the normally robust median values as a centrality measure in order to avoid correcting for outliers, we also had to correct for changes in sample types over time. Perhaps we cannot expect a laboratory to devote the time and skills necessary for such a complex analysis.

Based on the current study, we conclude that investigating the relationship between Lean interventions and performance outcomes, in terms of reducing time buffers, is a complicated affair. Despite our study being based on a substantial long-term dataset that was collected in a short-cycle repetitive environment with homogeneous groups of flow items, a high level of variability still exists. This raises questions for studies aiming to focus on Lean applications and resulting performance changes in other healthcare settings, such as

nursing wards, which are characterized by much smaller and more heterogeneous populations of patients.

As all research, our study has some limitations. It is possible that a time lag occurs between applying Lean interventions and their effects on performance. While we believe our longitudinal approach covers the important periods, it is possible that the real benefits lie further ahead. We have tried to address these possibilities through using interviews but, even in a longitudinal study like this, such uncertainties remain. Another limitation relates to the interviews that addressed events that had occurred three to five years earlier. Whilst we adopted recall-enhancing techniques, the human memory is not infallible. Additionally, there is always the risk that performance changes are attributed to the wrong root causes, despite our attempts to reduce this risk through triangulation with qualitative and quantitative data. Finally, we opted for a single case study approach because we had access to what is considered the leading Lean application in the Dutch healthcare field, and this allowed us to study performance over time. The downside is that this obviously limits the possibilities for generalization.

## **2.6 CONCLUSIONS**

This study investigated how the long-term application of Lean practices influences time buffers. In our specific case, we observed that the time buffer initially decreased and we attribute this to the reduction of artificial variability. However, interestingly, despite the laboratory's long Lean tradition, there was almost no *focus* on variability in this healthcare organization. It seemed that the role of variability was neither well known nor understood.

The study applied a robust and structured approach to determine changes in throughput time performance over time. During the review of the literature, it became clear that there is a lack of consensus on what constitutes Lean performance. Furthermore, available scales to measure Lean tend to address Lean implementation rather than performance outcomes. In our opinion, there remains a need for a generally accepted measure of Lean performance. From the perspective applied in this study, time buffer performance should play an important role in evaluating Lean applications in the service sector as it should reflect the effect of variability reduction.

Ultimately, our results show that an organization is able to increase its throughput time performance through Lean interventions. However, not all interventions lead to satisfactory results, and later interventions can distort or reverse earlier positive results. This raises questions as to the value of Lean-oriented studies that focus on short-term effects, and whether the effects they measure are sustainable. We would argue for a greater use of longitudinal studies that investigate Lean applications and performance, since one of the main challenges for organizations introducing Lean ideas is to sustain the initial gains whilst moving forward.