Technology Adoption in Consumer Goods Manufacturing in Asian, Low-cost Sourcing Countries
By
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Massachusetts Institute of Technology, 2012

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Abstract

With increasing cost of labor, additional regulatory pressures, and changing consumer habits, consumer goods manufacturers in low-cost sourcing countries in Asia are increasingly looking at manufacturing technologies to help. These manufacturing technologies in the apparel industry range from electronic sewing machines that have been around for decades to the precision control robotics that are still in the development phase. We aim to demonstrate the benefit of technology adoption and catalog the barriers faced in implementation.

To achieve this, the project first explores the extent of technology adoption within the Li & Fung supplier network through the use of the technical audit; a questionnaire which includes 5 technology related questions that are filled out on-site by a third party auditor. This analysis is then expanded through a vendor survey launched to hundreds of factories that asks additional questions around technology adoption. Finally, this analytical review of technology adoption is complemented by an in-depth design and implementation of a technology system, specifically an Industrial Internet of Things (IIoT) system, at a bottling factory. This study further demonstrates the potential impact of technology in factories and the challenges to implementation.

In demonstrating the benefit of specific technologies, we are able to show a statistically significant correlation of higher performance with two technologies from the technical audit. Through our IIoT project, we also simulate how an inventory buffer optimized with the data gathered by the IIoT can increase productivity by as much as 34%. Finally, we catalog financial, strategic, and organizational barriers that factories face.

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2. Introduction

2.1. Project motivation

Li & Fung is a global supply chain manager with thousands of manufacturing factories in its supplier portfolio. Its financial performance peaked between 2011-2013, based on total revenue and net income and both of these metrics have decreased every year since (Morningstar Financials 2017). This signals that the company has been faced with new challenges, discussed in the following sections, that it has not yet been able to solve. Li & Fung has, however, invested in a number of resources to help evaluate what could be done to address these challenges.

We form our hypothesis that technology adoption is an essential part of addressing these challenges, but we recognize that it cannot be done successfully independent of many other factors (e.g., sound operational practices). This hypothesis developed through site visits, interviews, and a review of technologies, which have demonstrated the ability to decrease lead-times, increase productivity, enable flexible order quantities and customization, and be more environmentally and socially sustainable. The purpose of this thesis is to investigate technology adoption to see how technology can be effectively applied to address the challenges Li & Fung is facing.

2.2. Challenges addressed

2.2.1. Economic pressures

One of the main benefits Li & Fung provides is their ability to find lowest sourcing cost for their customers. Often, this is through the lowest cost labor, which they have access to in areas such as China, India, and Southeast Asia. However, with the boom of these economies, labor rates have steadily risen and forcing tighter and tighter margins. This has been offset by a steady price deflation for products like textile apparel over the past 30 years, in large part due to companies like Li & Fung. As Figure 1 shows below, the average clothing price in the United States between 1983 and 2013 increased 0.8% per year while the average price in the United States for the same time period for all goods was 2.9% (Reed 2014). This means that cost of clothing increased at a lower rate than inflation and therefore we can categorize the trend as price deflation.   They have been able to consistently keep prices low for their customers through continuously finding lower cost suppliers. This, however, has reached a tipping point, where there are fewer and fewer places to find this low cost labor and prices are no longer decreasing. However, consumers of apparel and therefore Li & Fung's customers continue to expect and demand these low prices.

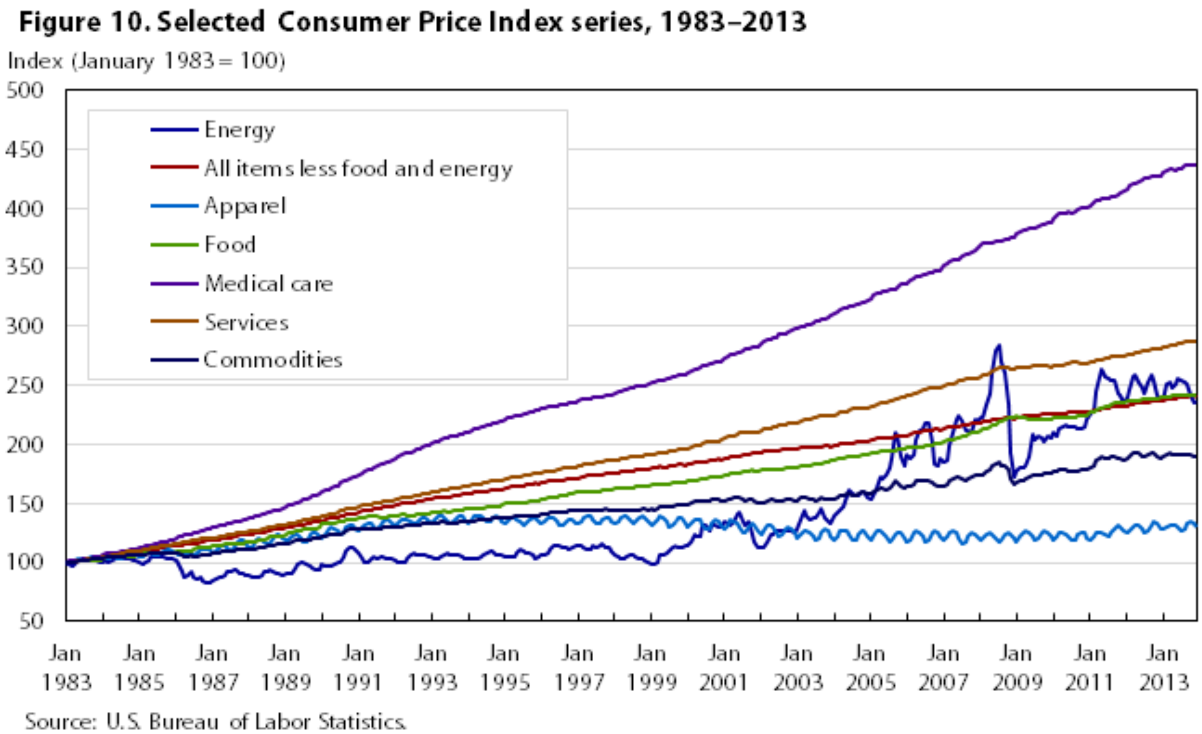

Figure 1: Demonstration of the price-deflation of clothing compared to other consumer goods

2.2.2. Regulatory pressures

In many of the countries where Li & Fung has its supplier base, there is minimal visibility into the working conditions of the employees. Some regulation does exist in order to ensure a standard level of working conditions, however the level of enforcement of these regulations varies tremendously. With a number of tragic disasters recently, including the Rana Plaza building collapse in Bangladesh in 2013, there has been much needed exposure to the working conditions of these workers (Chandran 2013). In addition, with workers gaining increasing access to the Internet and phones, there is more opportunity to ensure proper working conditions.

Li & Fung has committed to being a part of the solution with stricter enforcement and monitoring of the standards. This has narrowed their supplier base and also increased the cost for enforcement. More importantly, Li & Fung is always looking to see how they can improve in this area and be a leader for sustainable habits. For example, they have invested in the area of material and product traceability to ensure customers of the origins of the products.

2.2.3. Shifting consumer habits

Fashion is inherently a constantly and rapidly evolving industry that requires quick relatively short product development cycles and similarly short product manufacturing runs. Li & Fung has done a good job of building in flexibility to their supply base in order to match the expectations of the fashion industry. This includes understanding supplier capabilities and choosing suppliers based on their expertise with a specific fashion. In addition, very little capital investment is required to construct "cut and sew" lines and, by nature of the processes, they are fundamentally adaptable to changes in the clothing.

More recently, however, consumer habits have been shifting in a way that will require additional changes to the current system. Customers are looking more towards "Fast-fashion", defined as the rapid movement of fashions from the catwalk to the fashion retailers, which has actually been a phenomenon around for the better part of a decade (Bruce 2007). "Fast-fashion" requires a short lead time by definition, which puts strain on the supply chain. In addition, there is also a trend towards customization, although this is still a fraction of the market and has yet to hit the mass market. It is becoming more and more significant in certain large markets; in Converse's New York location, for example, had 10-12% of their business go through customization (Abnett 2015). This requires further capabilities in the supply chain in order to meet the rapid requested delivery dates of fast-fashion products or small order sizes for the customized products. This is where technology can help play a role by having equipment with rapid (or even instantaneous) changeover capabilities.

2.2.4. Internal challenges

In addition to these external challenges, Li & Fung also has internal challenges that make responding to the external challenges more difficult. One of the main challenges is that Li & Fung does not own the majority of the factories in its supplier base. Therefore, it is difficult to make quick and significant changes in the factories. It requires a lot of resources to convince factories of doing something differently and even then, it will only occur at the speed the factory desires. This is a particularly important point when we think of convincing factories to invest in additional technology.

Another significant challenge is that Li & Fung is a fragmented organization due to the history and nature of the business. It is a customer relationship focused business, meaning each customer division has a lead entrepreneur, referred to as “little John Waynes” because of the image of this entrepreneur standing in the middle of a wagon train and shooting at the “bad guys” (Magretta 1998). This has advantages, including distributed leadership, but it also results in a lot of siloes. Each part of the organization focuses on their key relationships and have less incentive to share or optimize amongst the whole company. Further adding to these siloes are the large number of mergers and acquisitions over the past couple decades, leading to many different systems (e.g., IT, business processes). Li & Fung also operates a number of distinct, but interrelated businesses; from distribution, to retail, to sourcing, which further siloes the organization.

2.3. Approach

In order to understand how technology adoption can address the challenges that Li & Fung is facing, it is important to understand the issues at both a high level (i.e., the supplier portfolio level) as well as at the individual factory level. Therefore, to get breadth in our research and understand the issues at the portfolio level, we analyze audit data and survey responses from as many factories as we can. Then in order to understand the subtleties at the individual factory level that might be obscured at the aggregate level, we also implement a project at a single factory and spend significant time there to understand depth as well.

For breadth, we begin by using existing data from factories. Li & Fung has a technical audit that they perform at factories, which asks over 200 questions concerning "technical capabilities" (e.g., number of machine X, number of employees). The technical audit is a newer audit and therefore has not been completed at all factories yet. However, the plan is to semi-regularly perform it at factories in order to update Li & Fung's understanding of the factories' capabilities. There are 5 questions that specifically related to automation/technology which are used as an initial indication of technology adoption. We use this as a base, in addition to a number of interviews with specific factories and site visits, to develop an online survey that we launch to a few thousand factories. We then use performance data to try to see what correlations existed between technology (data from both the technical audit and the online survey) and performance. These analyses are described in depth in section 5.

For additional depth, we select a Li & Fung owned factory in Thailand that produces, bottles, and packages various beauty products. We focus on a specific line in the factory that produces mouthwash for the Asian market. We choose this factory for a few reasons, including the fact that it is owned by Li & Fung directly and therefore we could have more influence on implementing a project, particularly given that the duration of this project is 6 months. We also notice after visiting this factory that they have a clear willingness to engage in improvement projects, proof is a number of existing improvement programs, and they have a dedicated team. We spent a week observing the factory and identifying a technology project to address one of their main issues of not being able to quickly the root cause of loss in productivity. Through the development of this technology project, we are able to learn a lot about the challenges faced by a factory adopting a new technology, as well as identify an impactful and beneficial technology system.

2.4. Project outcomes

There are a few main outcomes from this project:

- A quantified understanding of the penetration of a few key technologies within the Li & Fung supplier base
- A quantified assessment of the impact on performance for a few key technologies within the Li & Fung supplier base
- A list of the top challenges that factories face when implementing technologies, including factories’ expected return on investment
- Development of an Industrial Internet of Things system in a factory with complementary process improvements ideas (the most significant being a quantified impact for buffer)

3. Company overview

First it is important to understand the history of Li & Fung and the environment in which they became established. Although the entire industry and country has evolved drastically over the past century, the history that helped form the company in its values and management style has persisted in many ways.

3.1. Historical context

For much of the second millennium, China actively discouraged trade with Western countries, thanks in large part to the policies of the Ming dynasty. This began changing with the Qing dynasty and in 1684, the Kangxi Emperor began to allow foreign trade in four cities, including Guangzhou. In 1757, the Qianlong Emperor closed all other ports, leaving Guangzhou as the sole port of trade (Perkins 2013). There was a huge trade imbalance, with China exporting tea, silk, and porcelain, and importing very few European products, thereby requiring the British to part with precious silver in exchange for the Chinese products. This was not sustainable and led to the British instead using Opium from India through middlemen, which was not well received by China. This led to the First Opium War, which resulted in a decisive British victory, the Treaty of Nanking in 1845, and the cession of Hong Kong island. The Second Opium War, just 15 years later and ending in 1860, further solidified the presence of Europeans in China, including the ceding of Kowloon peninsula across from Hong Kong island (Roebuck 1999).

3.2. Li & Fung beginnings

With a foothold in Hong Kong, Guangzhou, and the rest of the Pearl River Trade, the European powers secured a flourishing trade network, out of which Li & Fung grew. Founded in Guangzhou in 1906, Li & Fung began as small export company, trading in products that the company itself manufactured: porcelain, fireworks, etc. The company took the names of its two founders, Fung Pak-liu and Li To-ming, who later sold his shares in 1946. The company moved to Hong Kong in 1937 and during the course of the war, would move all operations there and this would become the permanent base of operations (Bang-yan 2006).

Following the war, Li & Fung began to specialize in different types of products, mostly textile and plastics. By 1970s, the company was facing pressure as the rising Tiger economies of other Southeast Asian countries began to grow and Western retailers also grew in size and began negotiating directly with their suppliers. William and Victor Fung then took over (both of whom were educated in the United States) in order to modernize the company. Beginning in the 1990s, the company began a number of mergers and acquisitions in order to expand their supplier network and customer base, while also diversifying into other related industries as well. However, in the past few years, due to other pressures, they have been trying to focus on their core business of trading, which still includes a large array of soft and hard goods, and have sold or spun off parts of their business (Yung 2016).

3.3. Operating group context

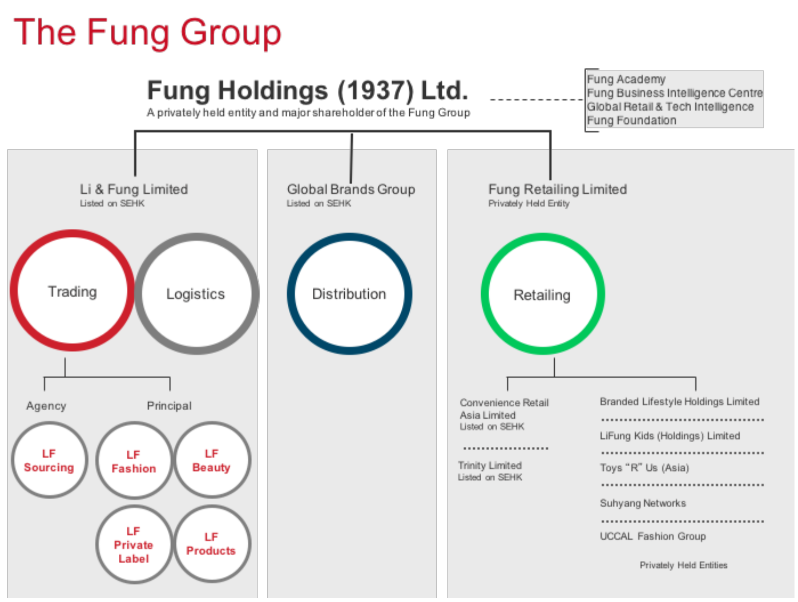

Figure 2: An overview of Fung Holding demonstrating the multiple parts of the business and Fung Academy as an indirect part of the business

3.3.1. Fung Academy

Particularly under the leadership of William and Victor, Li & Fung placed emphasis on Leadership Development, Sustainability Best Practices, and Innovation + Experimentation. The idea is that this group can help all of Fung Holdings (which is comprised of Li & Fung, Global

Brands Group, and Fung Retailing) move faster and adapt in this ever-changing world through catalyzing changes within the larger business. This is where the LGO interns, including myself, are housed for the duration of the research projects.

3.3.2. LF Sourcing

The main business is LF Sourcing, which represents the majority of the revenue of Li & Fung. LF Sourcing is structured with groups by region and country in order to have close contact with their suppliers. On the other end, they have merchandisers, which work closely with the customers to help ensure the correct requirements are met for the products requested.

3.3.3. LF Beauty

A much smaller business, but still over a billion dollars in revenue, is the LF Beauty business. LF Beauty actually does a lot of the product design (and packaging design) for their customers. They have a network of contract manufacturers where they source a lot of beauty products, but they also own and operate 5 factories themselves, meaning they have more control over any changes and are more invested to make operational improvements, as dollars saved directly benefit the Group.

3.4. Li & Fung business models

Li & Fung is structured to help serve the customers as best as they can. They are able to produce almost any product the customers request. From soft goods like apparel, which includes everything from knits like sweaters to wovens like men's suits, to hard goods, like furniture and accessories, which includes purses to sun glasses.

They are also flexible and offer two main sourcing business models. The majority of their business is the agency model, where Li & Fung acts as an agent for their customer. They negotiate a fixed margin with their customer, and then approach factories to negotiate a price. The other model is the principal model, where Li & Fung provides more of a full supply service, including product design and development through sourcing and production. They negotiate a price with their customer, but their margin is variable depending on what value-added services are provided and the price negotiated with the factories.

4. Literature review

4.1. Promising technologies for low-cost product manufacturing

We define technology broadly here as any piece of machinery or system that augments a human worker's (or group of human workers') ability to produce a product. This study focuses on technologies that we group into 9 technology areas after categorizing technologies together based on similar underlying mechanisms or functions. We develop these groups after a thorough evaluation of technologies in Li & Fung's factories and other factories as well. These technology groups represent a variation of technologies from cutting edge technology (e.g., robotics) to well developed and implemented technology (e.g., electronic sewing machines).

Electronic sewing machines: The basic mechanical functions of sewing machines has remained the same for the last half-century, however with the integration of electronics had advanced the use of the sewing machines (Jana 2004). Electronic sewing machines are those machines with such features such as automatic trimming that aids the worker so that they don't have to spend time in non-value adding tasks (such as trimming the thread in the example of automatic trimming). These are not computerized sewing machines (which are encompassed in computer controlled machines technology category), but rather simple sewing machines with electronic controls and some added functionality over the most basic mechanical sewing machines.

Specialized sewing machines: These are essentially electronic sewing machines, but with a dedicated purpose. They have additional mechanisms and machinery that complement the core sewing mechanism in order to accomplish a specific task. Three of the technologies asked about in the technical audit would be in this category, they are: auto placket machine, auto welt pocket machine, and auto collar machine. As their names indicate, they are focused on sewing a placket, welt pocket, and collar, respectively.

Whole-garment knitting machines: Knitted garments (versus woven fabrics) require a different fabrication process. The whole, shaped garment knitting machine was developed in

1995 and today still only comprises 11% of all knitted garments (Rajkishore Nayak 2015) . As the name indicates, these machines knit a garment in a single piece with no seams.

Computer controlled machines: Within the industry this typically refers to computer controlled cutting and spreading machines (as the name indicates, these machines spread out the fabrics and then cut them). Although this technology has been around for significant time, Gerber first introduced the GERBERcutter in 1969, which is often cited as a revolutionary invention,it is still perceived as cost-prohibitive for many factories (Lemelson MIT n.d.). Today this category also includes recent invitations, such as laser etching machines, which are used to pattern the jeans and can complement or replace the chemical washing process. As mentioned before, computer controlled sewing machines (i.e., where you can upload a pattern to be sewn) are in this category as well.

Other automated equipment –This category mostly entails automated equipment that does not fall in the other categories. It is where an operator loads work pieces into a machine which automates the task. This would include automated steamers and pressers (where an operator can simply load a pair of jeans, which takes seconds, to be steamed and pressed, which would normally take a few minutes for an operator). Other examples include a continuous fusing machines (which fuse pieces of clothing together) or automated folding and packing machines.

Conveyor systems: A number of factories are also attempting to move from batch processing (often referred to as "Progressive Bundle System (PBS)") to single piece flow (often referred to as "Unit Production System (UPS)") due to number of different benefits (including reduced inventory, faster cycle time, etc.). A common system is an overhead hanging conveyor system where each hanger has all the components for the garment.

Robotic arms: This is the most nascent technology category that is being experimented with for use in different areas, including spraying the chemical bleaches onto jeans or physically abrading the jeans to create patterns (Jeanologia n.d.).

Real-time digital data capture: With improved data storage and data analysis techniques, having real-time information on production can have numerous benefits (e.g., root cause for efficiency loss, balancing lines, quality issues). There are a few systems, one of which that Li & Fung is currently testing in a few garment facilities, which use RFID tags to track data in real-time along the steps as a garment is assembled.

Advanced water technology: Some factories that have washing facilities, which is very important for denim, are implementing technologies to reduce their environmental impact. One example is a waterless ozone wash for denim.

4.2. Technology adoption in factories

There exist a number of frameworks under which companies evaluate when and if a technology will be ready for adoption within the company. For example, technology readiness levels (TRLs), which were first developed by NASA in the 1970s (Banke 2010). These are useful to think about for some of the newest manufacturing technologies (like 3D printing) and to a lesser extent robotic arm systems, which though common in other manufacturing realms, are only recently being implemented by the garment industry. These newer technologies are likely still in levels 6-8 ("Prototypes and some initial successes") out of 9 of the TRL, but most technologies discussed have been at level 9 ("Technology proven through successful operations") for a while.

Therefore, for the technologies that do exist, a better framework is to think about the factors (and how to overcome them) that are preventing the adoption of the technology, including: organizational barriers, financial barriers, and strategic barriers. Organizational barriers are typically management's resistance to change or a bureaucracy that requires too much time to make changes. Financial barriers are whether the investment in the technology will be profitable within the firms expected duration of return on investment. Strategic barriers are the direction of the company and whether the technology investment will enable the company to follow its short and long-term strategies (e.g., shift into new industries, react to change in consumer demands) (George W. Mechling 1995).

5. An analytical review of technology adoption in Li & Fung factories

We take an iterative approach to analyzing technology adoption at Li & Fung. We begin by using existing data at Li & Fung (the results of the technical audit) and follow this with a survey we develop to expand on hypotheses developed through the analysis of the existing data.

5.1. Technical audit

Li & Fung trained auditors conduct a technical audit of all factories semi-regularly (whenever an update is needed). They walk around the factory and record the answers to a list of over 200 questions. The fidelity of the answers therefore is assumed to be higher than a self-reporting survey because it is objective and not influenced by factory and, therefore, the audit results are a resource for us to better understand the capabilities of the factories.

The process is several years old and come out of a need to understand some of the technical capabilities of factories. So far 700 were audits have been completed with only a few being repeated. Ideally with unlimited resources, these technical audits would be conducted regularly to all factories. Specific questions were selected based on identifying what facts about factory capabilities merchandisers would want to know to decide to which factories they should route specific orders. Of the 200 questions, five questions are particularly relevant to this study because they concern "automation", which serve as a proxy for technology in factories. These are not cutting-edge technologies, but have been around the industry for more than a decade.

1. **Computer Aided Design system available for grading and marker making… (CAD)**. This is used to layout the cutting pattern on the fabric to minimize the loss fabric and maximize quality (e.g., stripes lining up on shirts)
2. **Automatic spreading machine with tension free available in factory… (AutoSpreader)**. This is used to automatically spread the fabric along cutting tables before it is cut.
3. **Auto placket setting machine (AutoPlacket)**. This is used to automatically set the placket (the double layer of fabric where the buttons of a shirt are) on the shirt and sews it.

4. **Auto welt pocket setting machine (AutoWelt).** This machine automatically forms and sews a welt pocket on a piece of clothing.
5. **Auto collar sewing machine (AutoCollar)**. This machine automatically forms and sews the collar of a shirt.

We look at these five questions to see what the adoption of these technologies are at the factories with technical audits. The auditors can select either "yes", "no", or "not applicable" for each of the questions. Figure 3 below, shows that there is a relatively high penetration of these technologies. Almost 75% of factories have 100% of the applicable technologies, but this still leaves more than a quarter of factories missing at least one of these rather basic technologies. As mentioned previously, these five technologies from the technical audit are well developed so it makes sense that a high number of factories have "full" adoption for these technologies.

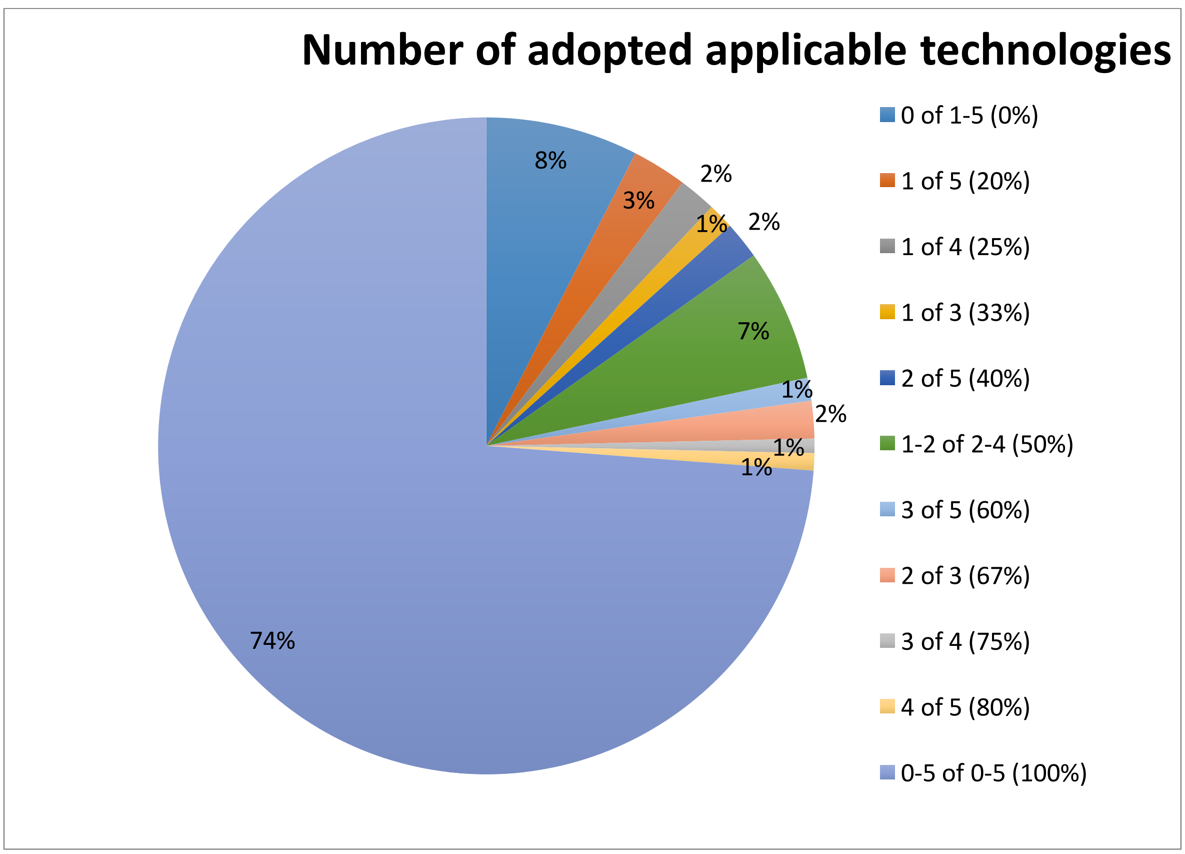

Figure 3: The relative adoption of the 5 technologies asked about in the technical audit

There are a number of hypothesis that can be tested concerning why these factories do not have "full implementation" of these 5 technologies. They might be strategic, financial, or organization barriers. We conduct a follow-up survey to test a number of hypotheses.

We then use the technical audit data in conjunction with performance data of these factories to test our hypothesis that factories with technologies exhibit greater performance. Performance is measured and tracked at Li & Fung; an overall performance score is calculated from a combination of factors, including quality, on-time delivery, etc.. Of these 706 internal audits, we have performance data for 595 because of a mismatch in the IT system. The performance evaluation is structured where by 22 different metrics, subset into 5 categories (delivery, production accuracy, compliance, quality, and documentation), are used to create an overall performance score based on categorization and weighting of the scores from these 22 metrics. This calculation is a propriety Li & Fung calculation and is optimized every few years in order to keep it accurately reflecting the performance of factories. Figure 4, below, shows that the average of overall performance score (again, a propriety calculated metric by Li & Fung from numerous performance metrics) for factories with a technology is higher than those without the technology. Although this seems promising, we test these hypotheses in order to understand the statistical significance of these results.

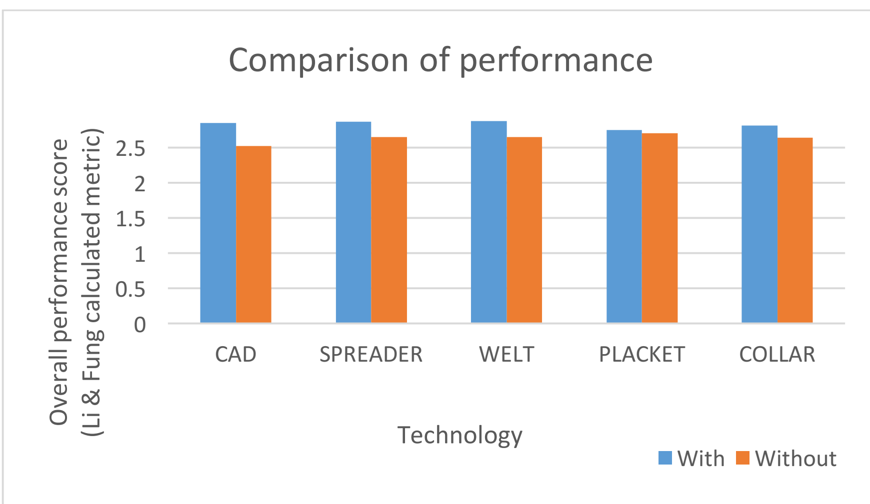

Figure 4: Demonstrating the difference in average overall performance for factories with and those without each of these 5 technologies

In order to test the statistical significance, we use the R statistical data package, to conduct paired different test, where our null hypothesis is that the means are the same. We then run a student's t-test to generate the statistics seen in Table 1 below. We do this for the overall performance, as well as 5 of the 22 metrics for which we have the most reliable and complete data (based on a qualitative assessment of the data).

$$t - statistic = \frac{(\overline{x_1} - \overline{x_2}) - (\mu_1 - \mu_2)}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}}$$

Equation 1: The equation behind the t-statistic, which is then converted to a p-value based on the student's t-distribution. $\overline{x}$ is the mean of the sample data, $(\mu_1 - \mu_2)$ is the difference in means we are testing (which we assume to be 0), s is the sample standard deviation, and finally n is the number of samples in the sample set.

	Overall	Shipped on time by PO	Shipped on time by qty	Lateness impact on FOB	Shipped on time by FOB	Lateness impact on qty
CAD	1.83E-06	1.05E-04	6.51E-06	4.13E-05	1.98E-05	4.72E-05
AutoCollar	9.56E-02	8.42E-02	1.89E-01	4.83E-01	1.47E-01	5.64E-01
AutoPlacket	6.52E-01	7.26E-01	8.59E-01	9.63E-01	7.42E-01	9.69E-01
WeltPocket	2.76E-02	2.12E-01	2.94E-01	6.23E-02	2.89E-01	6.51E-02
AutoSpreading	7.62E-04	5.06E-02	3.51E-02	1.00E-03	4.28E-02	7.81E-04

Table 1: From technical audit, P-values of confidence in difference of means. Those highlighted in green are less than alpha = .05, which would indicate at least a 95% confidence in the difference in means of overall performance between those with a technology and those without.

Based on Table 1 we can say that factories with CAD or AutoSpreading have a statistically significant (with greater than 95% confidence) higher performance compared with those factories without these technologies.

However, correlation does not necessarily imply causation. The question is whether because a factory has the equipment, it performs better, or rather that because the factory performs better, it therefore can purchase the equipment. There are likely many compounding factors for factory performance and technology adoption. In order to understand this, we would need further tests. For example, we could compare a factory before and after it had equipment or compare similar factories (in terms of size, types of products, etc.) for those with and those without technology. This would all require data that does not currently exist at Li & Fung, but can be obtained partially for example, through an expanded technical audit over time.

5.2. Vendor survey

Following our initial study based on the technical audit, we build a survey with the following objectives: inquire about the percentage adoption for additional technologies not covered in the technical audit, understand the barriers to technology adoption, and understand the motivation behind technology adoption.

The survey is developed in SurveyMonkey and is included in an IT survey that asks detailed questions about various software implemented. It is provided in both English and Mandarin, for those sent to China. It is launched to 2,738 apparel factories, split into 412 of the highest-volume by revenue suppliers and the remaining 2,326, covering 21 countries and representing a range of customers and various apparel products. A total of 747 responses are received including 196 partial responses and 551 complete responses, and for which 508 have performance data in the Li & Fung database. The surveys were emailed to factories asking them to help Li & Fung better understand the factories IT and technology. There was no incentive or repercussion for not filling out the survey, but the strategic partner factories did have country managers follow up if the survey was not completed. A screenshot of a few of the questions is shown in the appendix.

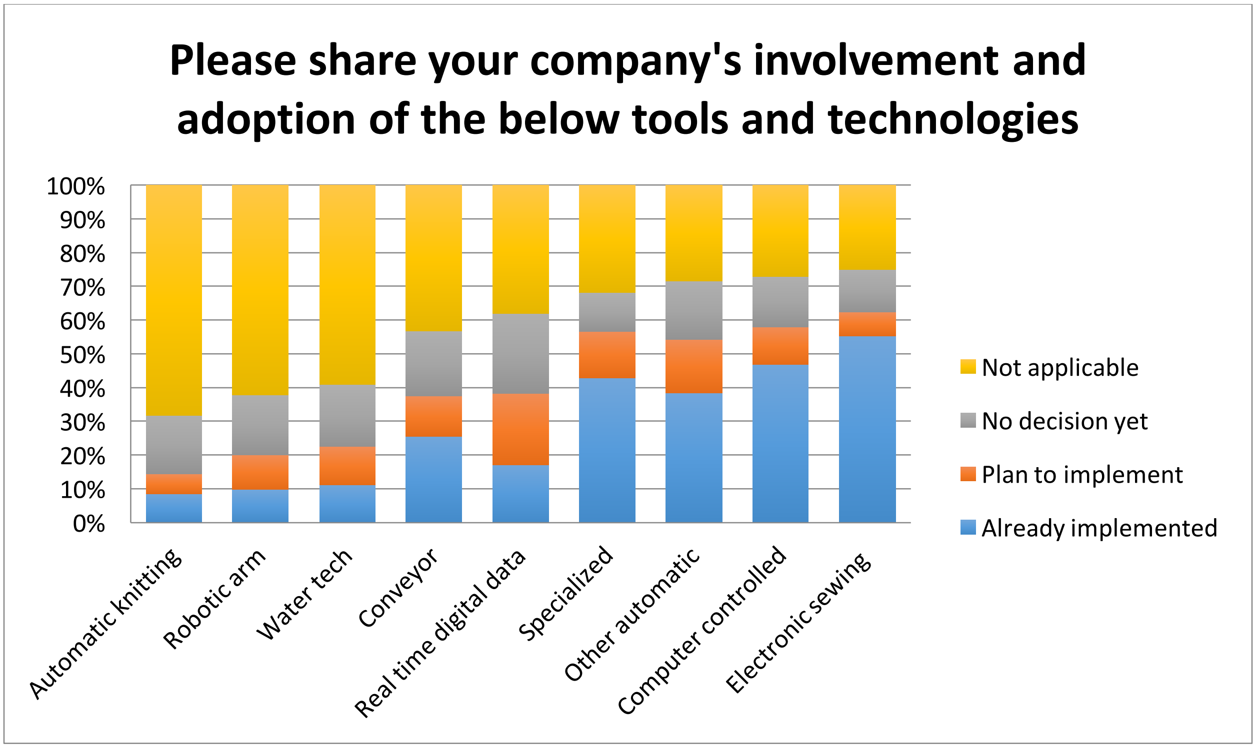

Figure 5: Overview of the relative adoption of each technology demonstrating a large percentage of factories reporting a technology as "not applicable"

Based on the results from the technical audit (which asked about 3 technologies within the "specialized sewing machines" and 1 technology in the "other automatic equipment), we would expect similarly high levels of adoption for those categories. However, we see overall relatively low adoption for all technologies. We also see much higher "not applicable" responses than we would hypothesize, further indicating that either factories did not understand what was meant by these listed technologies, or that they do not see the applicability yet of these technologies (e.g., they do not see how robotic arms are applicable). This is an area of opportunity for Li & Fung to either improve surveys in the future to ensure accurate comprehension, but also to ensure that factories are appropriately informed and educated about all technologies.

5.2.1. Performance correlation with technology adoption

Similar to the analysis for the technical audit, we analyze the responses to see if there is a correlation between the adoption of technology and performance metrics.

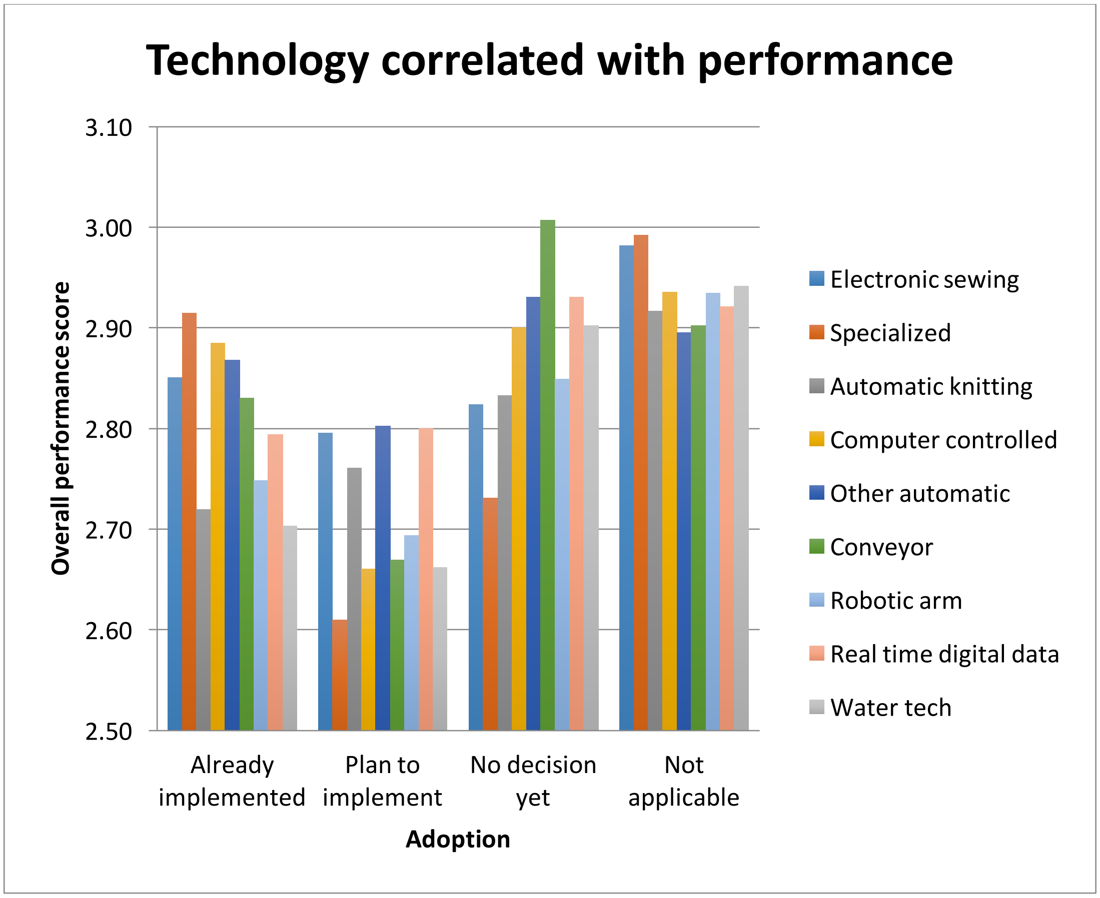

Figure 6: Comparison of overall performance score for various 9 technologies in vendor survey shows no visible trend

We can visually see that there is significant variation in the data and no discernible pattern. In order to identify whether there is a statistically significant difference in the means, we run a similar analysis to that which was run for the technical audit data. Table 2, below, shows the resulting p-values from the t-tests run for each technology and matrix.

Technology	Overall	Shipped on time by PO	Shipped on time by qty	Lateness impact on FOB	Shipped on time by FOB	Lateness impact on qty
Electronic sewing machines	0.291	0.344	0.854	0.492	0.609	0.584

Specialized sewing machines	0.292	0.390	0.913	0.412	0.932	0.686
Whole-garment knitting machines	0.669	0.005	0.772	0.874	0.575	0.529
Computer controlled machines	0.623	0.133	0.097	0.138	0.600	0.037
Other automated equipment	0.626	0.407	0.165	0.213	0.623	0.034
Conveyor system	0.707	0.111	0.177	0.122	0.758	0.947
Robotic arms	0.636	0.642	0.839	0.164	0.235	0.645
Real-time digital data capture	0.630	0.650	0.748	0.164	0.115	0.537
Advanced water tech	0.483	0.529	0.866	0.837	0.256	0.671

Table 2: From vendor survey, P-values of confidence in difference of means. Those highlighted in green are less than alpha = .05, which would indicate at least a 95% confidence in the difference in means of overall performance between those with a technology and those without.

We see that unlike for the technical audit analysis, there is no statistical significance to the difference in means for the performance data, only a few statistically significant results, but no evident pattern). This brings up uncertainty in the reliability of the results from the survey; it could be that since the factories were able to answer the survey themselves, there might have been different interpretation of the technology or potential falsification (purposeful or not) of the responses.

5.2.2. Factors that influence technology adoption

The survey includes a number of additional questions and information about the factories designed to better understand the factors that influence technology adoption. Specifically, I look at the following questions: 1. Whether the factory has an in-house design department, 2. If the company has a fabric platforming capability (the ability to make designs after purchasing large amounts of fabric, instead of the other way around), 3. If the factory uses Product Lifecycle Management (PLM) software, 4. ROI –Return on investment period, 5. Whether the factory would recommend LF (above 5 on a scale of 10) to other factories or detract (below 5 on a scale of 10) Li & Fung to other factories, and 6. If the factory has implemented lean programs. In addition to correlating these questions with technology adoption, I also test for correlation with technology adoption for country, customer type, and median annual turnover of the factory.

To perform this correlation, I use the statistics data package "R" and run a logistic regression on these variables. The p-value (which we use before to demonstrate our confidence in whether there was a statistically significant variation between means) is used in a functionally similar way to demonstrate the confidence in whether the coefficients of the logistic regression are significant or not. Table 3 below, shows the coefficient and those with high confidence are highlighted in green (p-value < 0.05) and somewhat high confidence are highlighted in yellow (0.05< p-value < 0.1). The full tables of all the factors are listed in the appendix.

	Electronic sewing	**Specialized**	**Whole garment**	**CNC**	**Other automation**	**Conveyor**	**Robotic arms**	**Real-time digital data capture**	**Advanced water tech**
Lean programs	0.7	0.3	1.0	0.2	1.1	0.8	0.4	1.4	1.6
Promoter	0.7	0.6	0.1	0.7	0.3	1.0	0.5	0.6	0.3

Table 3: Factors with at least 1 significant coefficient (p-value <.1) under logistic regression. The other 4 factors showed no correlations.

As we see from the truncation of the table, there were only two somewhat significant factors that correlated with the adoption of technology. If factories have other "lean programs", then they are more likely to have adopted technology. And if factories are "recommenders" of Li & Fung, they are also more likely to have adopted technology. There could be a number of reasons for this, but this could potentially be because factories that recommend Li & Fung have more interaction with Li & Fung and therefore have benefited from knowledge of other technologies.

5.2.3. Barriers to adoption

In order to understand what barriers to adoption might exist (and whether they are financial, organization, or strategic barriers), we ask factories about their greatest implementation challenges. We create a shortlist of 9 reasons based on Li & Fung's previous experience. We recognize that there could be bias here and potentially other reasons, but this provides us at least some sense of the barriers. This can be seen below in Figure 7.

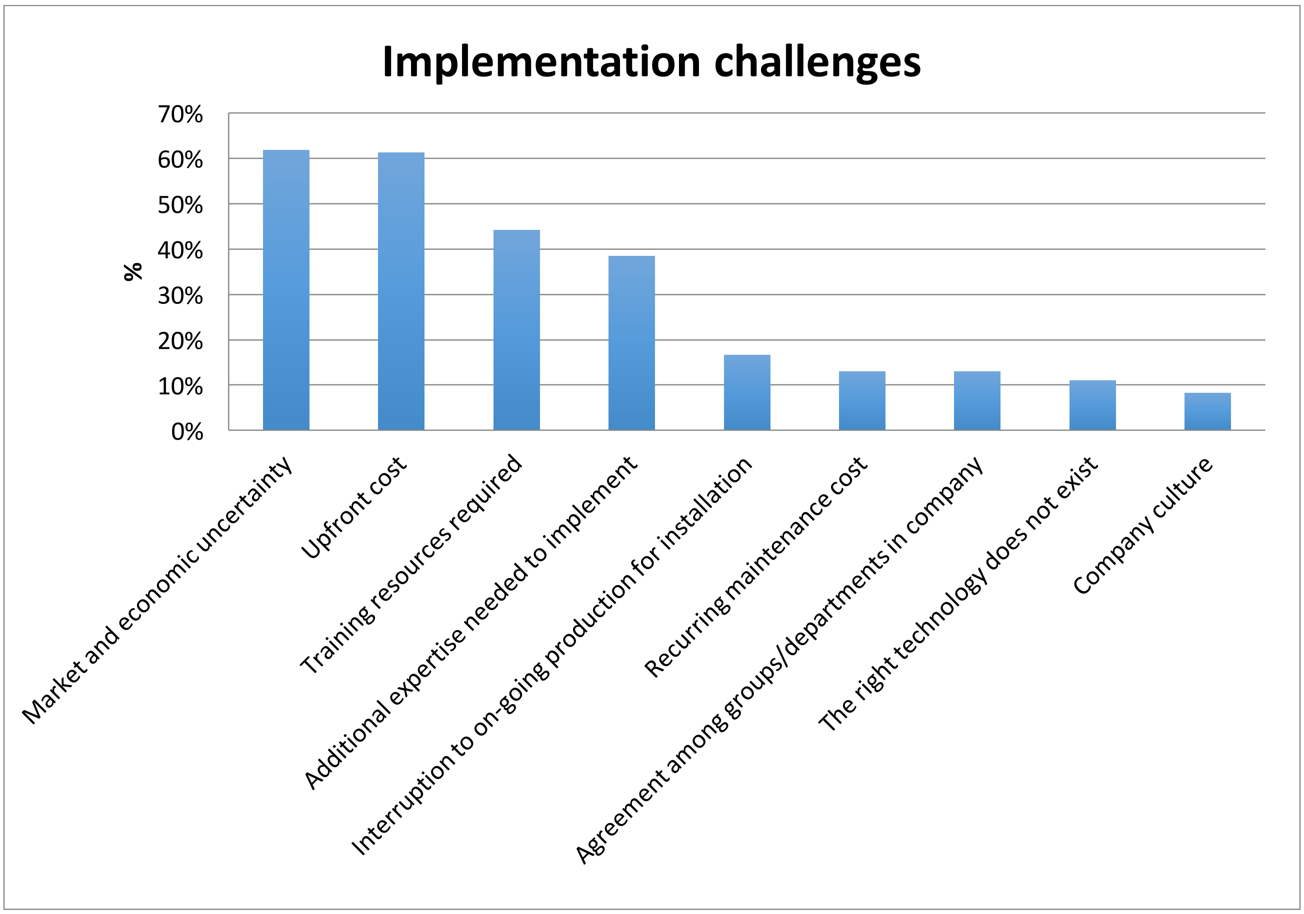

Figure 7: Implementation challenges factories face when adopting new technology

We can see that financial and strategic barriers are the greatest barriers to technology adoption. Organization barriers, at least self-reported, are not listed as one of the implementation challenges.

To further understand the financial and strategic barriers, we also ask about the return on investment (ROI) that factories expect when they implement a new technology. Figure 8 below shows what factories report for ROI when given the choice to select between <6 months, 6 months to 12 months, 1 to 2 years, or after 2 years.

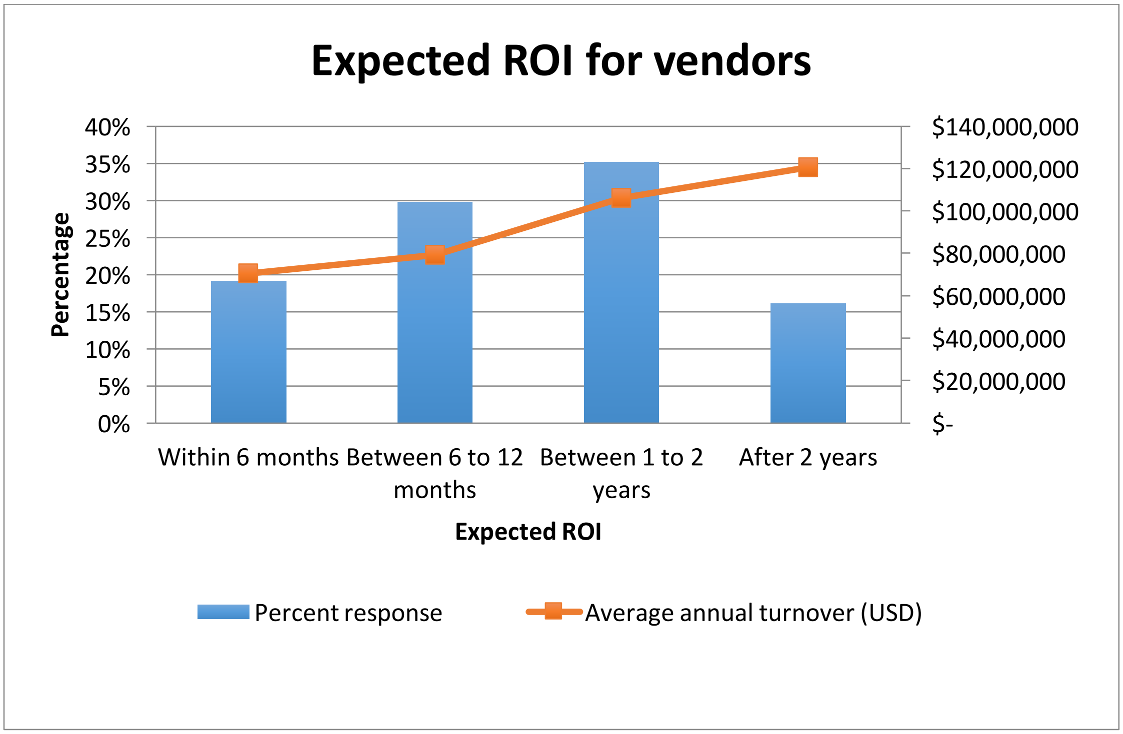

Figure 8: Expected ROI of factories shows a trend of a longer expected ROI with companies that have higher annual turnover

We see that there is a variation of expectation for ROI, but that the two-thirds are between 6 months and 2 years. We also see an intuitive correlation that the larger the factory (i.e., the larger the annual turnover), the higher their expected ROI.

5.2.4. Conclusion

From this survey, we learn a number of things about technology adoption in factories. Primarily, we see that there might be some limitations to having factories self-report what technology they have implemented. This likely indicates that the best way to ensure accurate reporting of adopted technology is to include it in technical audits. The technical audit is a good avenue in which Li & Fung can ask more detailed and specific technology questions to factories and not have self-reporting bias.

We see some correlations, however, including the correlation between a factory having lean programs and having the manufacturing technologies. This can indicate that Li & Fung should couple the two programs together when helping factories invest. Li & Fung can further investigate this point by asking additional questions in factories about lean programs, for example in the technical audit.

Finally, we see that factories biggest barriers to implementation are financial and strategic barriers. This is coupled with the fact that the smaller the factory, the shorter their expected ROI. Li & Fung can help reduce this barrier by offering financial resources to help cash-strapped factories.

6. Implementation of Industrial Internet of Things (IIoT)

6.1. Motivation behind IIoT project

After taking an analytical approach to understanding technology implementation in factories and developing a broad perspective, we then take a more in-depth look at one of the key technologies, specifically real-time digital data capture, which is enabled by IIoT devices. We choose this technology because of the recent innovations in the area and the need for additional insight provided by production level data.

6.2. Overview of the factory

The factory chosen for the project is one of the few factories owned by Li & Fung as part of the LF Beauty business. There are only a handful of factories, with the two largest in Thailand and the UK. The products that they produce range from soaps to scented candles to mouthwash. We focused on the OralCare (i.e., mouthwash) part of the factory in Thailand because they were already high performing and stable (therefore more willing and ready to try new technologies), but they were still looking to increase productivity and efficiency in order to increase the production capacity and serve more additional customers.

The OralCare factory is relatively automated, with empty bottles placed manually at the beginning of the line and then boxes of filled and packaged bottles removed manually at the end of the process, with most things in between being automated (although still requiring significant number of technicians and operators to operate the machines). The bottles are cleaned, filled with mouthwash, capped, labeled, safety sealed, shrink wrapped in groups, boxed, and finally palletized.

This automation, however, relies on the continuous operation of the equipment in order to be productive. When visiting the factory, we directly observed unplanned line shutdowns rather often and heard reports of difficulty with stoppages. The factory is targeting to increase its overall equipment effectiveness (OEE) by 6-8% in order to increase overall production capacity to meet potential forecasted increases in orders.

Although there is an effort to record the reasons for loss of OEE, it is done manually by operators, hence only high level information is available including approximate time of shutdown and restart and high level root cause. In order to improve the OEE of the system, however, more detail is required in order for the technicians and operators to know quickly the root cause of the issue. For now, they might only know that there is a problem with the filling machine, but in the future, they might be able to know which specific nozzle is causing the problem. This additional level of detail for loss of OEE was one of the main drivers for this project. Figure 9, below, shows the hierarchy of OEE calculation and OEE loss that are developed in conjunction with the factory.

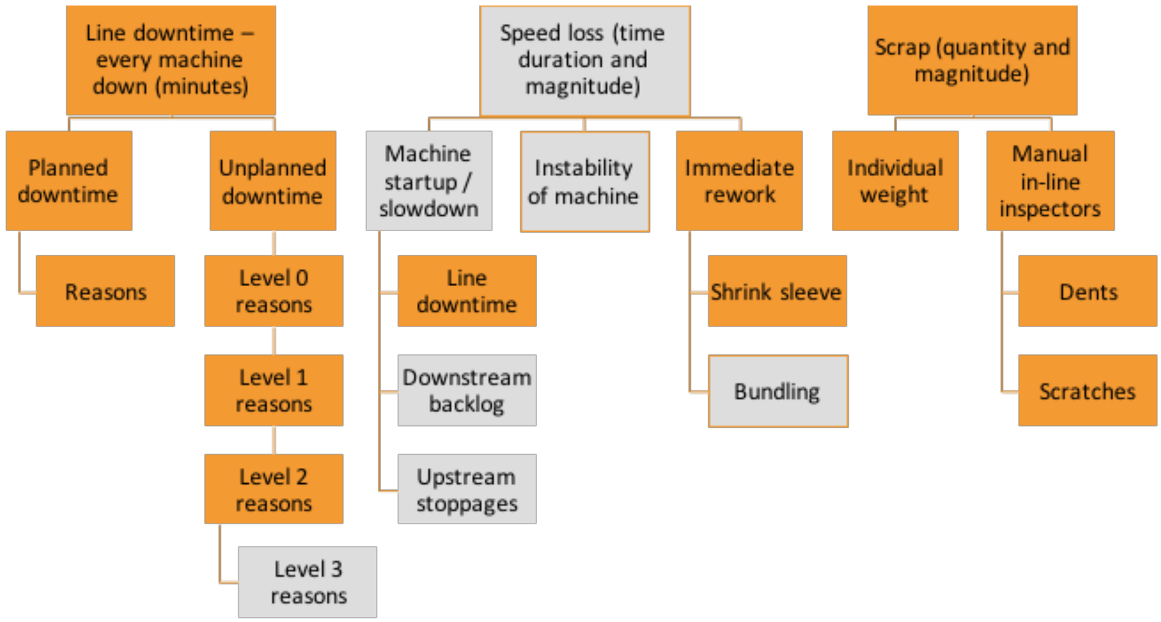

Figure 9: Current calculation for OEE (top) and breakdown for loss of OEE (bottom). The grey is what is not currently measured and the orange is how things are currently measured.

In addition, currently the OEE can only be calculated at the end of a shift once the manual sheets recording down time and the total number of boxes produced is counted. This is prone to human recording error and delayed by 8+ hours, meaning the information cannot be used in real-time to make improvements. Having this number in real-time can have a number of benefits, including improved planning, more immediate reaction to down-time, etc.

6.3. Current systems

The plant had implemented a related project a year earlier, which was used for "poka-yoke" (i.e., mistake proofing) in the weighing room for the mixing of the mouthwash to ensure that the correct amount of each ingredient was weighed for the right orders. The operators were instructed to scan each recipe that they were mixing and then scan each ingredient and the scale every time they weighed an ingredient. This was a relatively simple IIoT project that required only connecting the weigh scales to the computers.

The line is currently equipped with of sensors in-line, which are required for the automation operations. Most are internal to the machines (e.g., limit switches to detect completion of a movement on a machine), but there are also a number of external sensors as well. Figure 10 below shows the line and example of the types and locations of these sensors. Predominant are infrared (IR) sensors that detect the presence of a bottle and which are used to stop a machine if there are insufficient bottles us-stream or if too many bottles are building up down-stream. There are also scales that weigh the bottles immediately after filling and another at the end that weighs the entire box. Cameras verify that that the cap is securely applied and that labels are also applied correctly and have the correct date printed on them. There is also a sensor to verify that the safety seal is placed on the cap before it is heated. Finally, bar code scanners make sure the bar codes applied are correctly. All of these sensors read a significant amount of information in real-time, but the data is neither stored nor easily accessible, they are only connected locally to the appropriate machine's PLC (programmable logic controller).

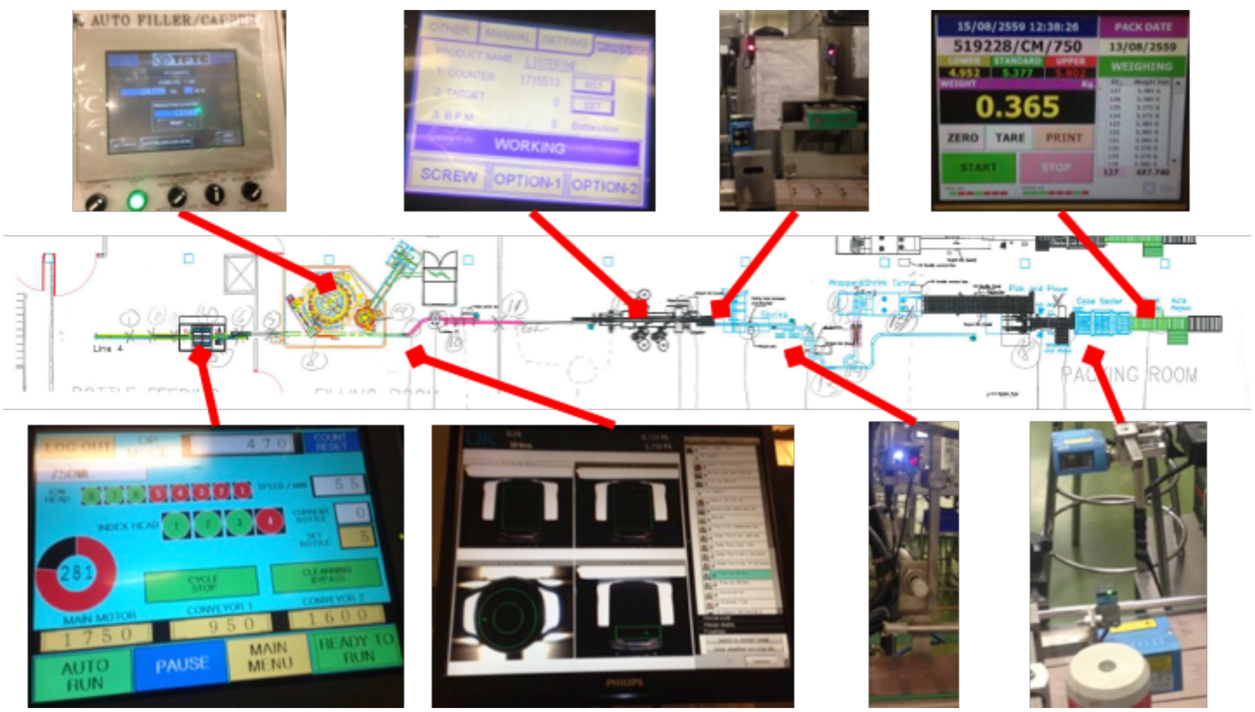

Figure 10: Overview of one of the lines with call outs for examples of where and what type of sensors exist.

The types of sensors, the types of PLCs, locations, and other technical information is important to catalog because they are the technical constraints for the designed system (i.e., what is technically feasible). In this cataloging process, we identify 40 sensors (mostly on-off sensors and bottle counters) that are important for the IIoT system. Ideally, sensor data would be accessed from the PLCs via a master computer, however many of the PLCs are older models which do not have the appropriate circuitry to record and transmit information and modification (or replacement) was not feasible. Therefore, we designed a system independent of the current PLCs.

6.4. System design

The approach to the system design is to move backwards. We first design the output, i.e., the functionality of the system, and then work backwards to figure out the system that is needed in order to have this functionality.

The first step we take is to select the critical parameters that would allow OEE to be measured in real-time as well as provide a more comprehensive OEE breakdown. We use Figure 9 from above with slight modifications to design the computer-integrated-manufacturing (CIM) management layout, shown below in Table 4. This is the output report that we are aiming to build. With this in mind, we are then able to back solve for the system that needs to be designed in order to support this report.

2. CIM Management Layout

This layout are used for management the production result. The Screen of management layout are consist of the following data.

1. Overview of packing line
2. Energy using
3. Production Data
   Summary of finished production
   a. OEE,OR
   b. Defect
   c. Design Speed VS Actual Speed
   d. Plan, Actual, Good, Reject
   e. Total time
   f. Etc.
4. Loss Time
5. Weight Sampling
6. Weight Checker
7. Cp/Cpk
8. Case/Palletizer
9. OEE/OR chart and report
10. Maintenance
11. Changeover
12. Bypass Logging Machine
13. Production Plan
14. Employee Plan
15. Employee management
16. User and Password
17. Production Error Edit
18. Master Data
19. Calendar of work

Table 4: Layout of the CIM management report

Based on the constraints previously discussed, we then outline the technical requirements of the system in order to reduce the risk to the system in implementation. This can be seen below in Figure 11. We include a potential option to connect the reporting to the Cloud so that anyone outside of the factory (e.g., the president of the group) could see the metrics, however this is not the core functionality we are trying to build.

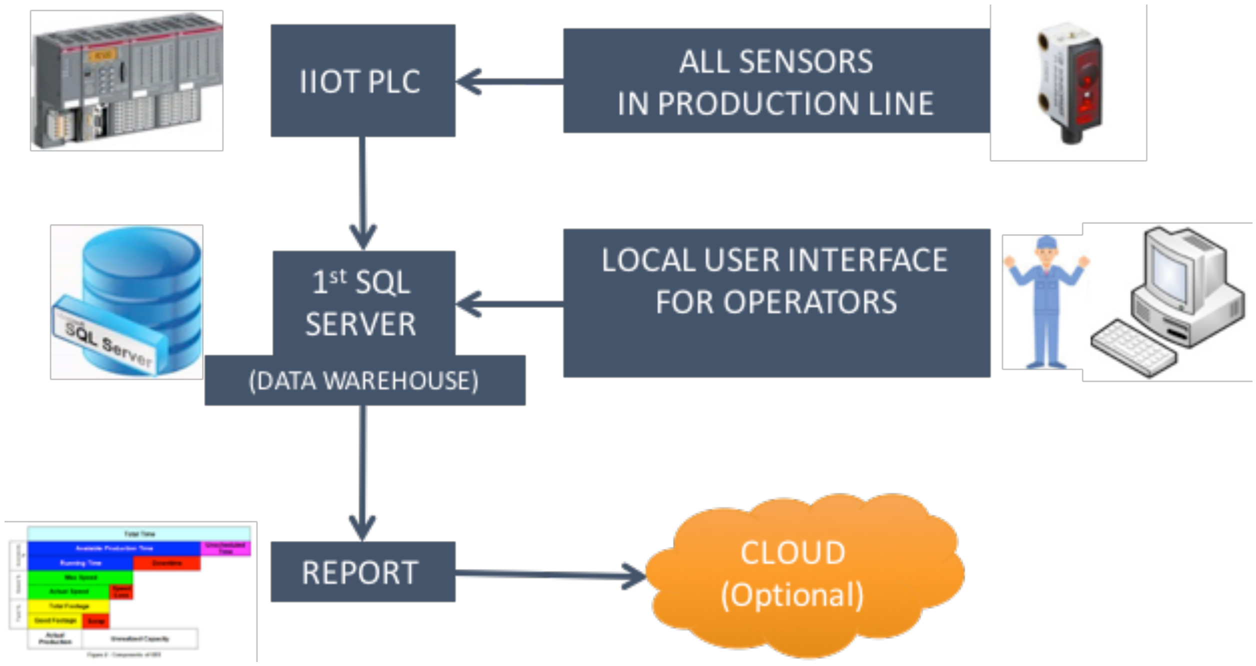

Figure 11: A high-level overview of the IIoT system

With the system outlined and developed, we proceed to work with a systems integrator, who has worked with this factory before, in order to implement the system. They provide the technical resources for sourcing the equipment and along with the technicians at the factory, to install the equipment. They also develop the user-interface application.

6.5. Results from pilot (time-study)

To best understand tangibly how the IIoT system will benefit the productivity, a time-study is performed. It is meant to simulate the information gathered by a single IR sensor. We choose a sensor immediately following the bottle filler. We use an application that will give a time-stamp every time the mouse is clicked. We click for each bottle that passes and can therefore calculate the productivity over time. We use a 30-second window to calculate the production speed in the graph below Figure 12.

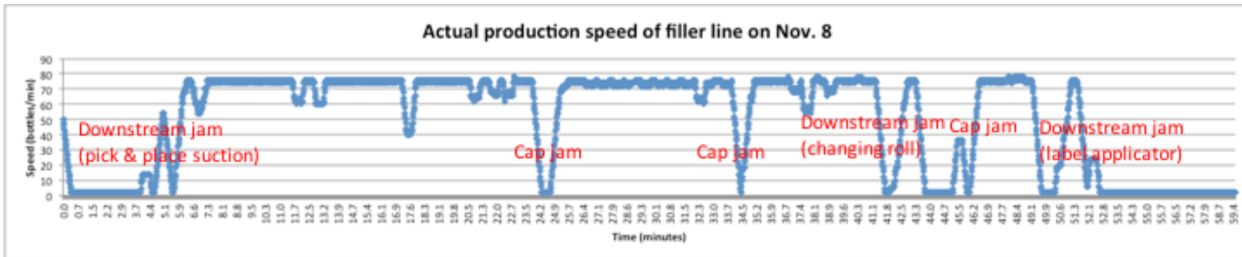

Figure 12: Graphical representation of the production speed of the bottle filling machine over a one hour time

Based on this graph, we can overlay the reason for loss of production speed (inserted here manually in red text). We can immediately develop recommendations from just this one-hour time study. For example, we see that two-thirds of the speed loss was from upstream or downstream jams (and that these jams caused an average of 156 seconds of downtime for the filler). We also see that there were repeated cap jams (with an average of 22.2 seconds of downtime for the filler). Although this is only a snapshot of time, it gives the Thailand beauty team an idea of the magnitude of where to focus their efforts.

6.6. Process improvement ideas

The IIoT project allows real-time OEE calculation and a detailed root cause analysis of the loss of OEE. However, the real benefit (e.g., productivity increase and the resulting financial increase) comes from the process improvements, which are informed by the IIoT system. There is a long list of potential process improvement ideas developed in collaboration with the factory team during the course of this project (e.g., using information to better coordinate changeovers, correlating nozzle number with scale to know if a single nozzle is causing issues).

The single most impactful process improvement idea, however, is the idea of adding an optimal amount of inventory buffer at key places along the line. This idea was developed through observation of the impact of a single machine shutdown on the whole line. Although traditionally we think of work in progress inventory buffer as something to try to minimize, there is an optimal level. We observe how two-thirds of the downtime for a machine was caused by upstream or downstream jams. Much of this would have been eliminated with an appropriately sized buffer, which would allow time for the jam to be cleared. We observe anecdotally that there isn't a single problematic machine, but rather all machines have an approximately equal likelihood of failing. This gives us confidence to investigate the impact of an inventory buffer on the productivity, based on the data from the time-study as, a proxy for the potential impact.

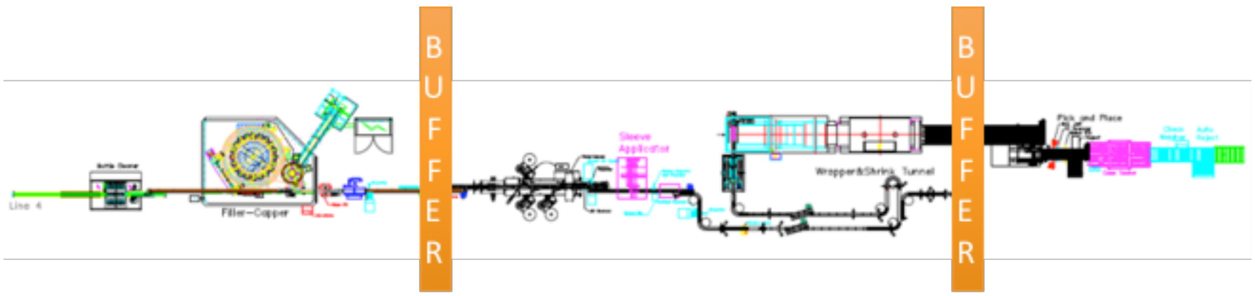

Figure 13: Assumption for the line is a 3-machine process (bottle cleaner + bottle filler, labeler + shrink wrapper, final packaging) with inventory buffer in-between the three machines.

$$Productivity_{zero-line\ buffer} = \frac{1}{\tau}\frac{1}{1+\sum_{i=1}^{k}\frac{MTTR_i}{MTTF_i}} \leq \frac{1}{\tau}\prod_{i=1}^{k}\frac{MTTF_i}{MTTF_i + MTTR_i}$$

Equation 2: Governing equation for determining the productivity of a zero-buffer line with *i* number of machines, τ is the production speed of a single machine, MTTR is the mean time to repair (i.e., the average down-time) , MTTF is the mean time to failure (i.e., the average up-time)

$$\mathrm{Productivity}_{\text{infinite-line buffer}} = \min_{\mathrm{i}} \frac{1}{\tau_{\mathrm{i}}}\frac{\mathrm{MTTF_i}}{\mathrm{MTTF_i}+\mathrm{MTTR_i}}$$

Equation 3: Governing equations for determining the productivity of an infinite buffer line with *i* number of machines, τ is the production speed of a single machine, MTTR is the mean time to repair (i.e., the average down-time) , MTTF is the mean time to failure (i.e., the average up-time)

We assume that each machine had the same production speed τ (currently all machines are set to the same production speed in order to balance the line, but this can be changed in the future with inventory buffers) of 75 bottles/minute. We then used the MTTR of 22.2 seconds and MTTF of 141 seconds from the time-study of the bottle-filler for all three machines. We recognize the limitation of this assumption, but absent of additional data, it provides a directionally correct answer. When we plug in these numbers to the zero-line buffer (which is the current system), we get a modeled production speed of 48.3 bottles/min. This is actually a validation that the model is representative of the system since the measured actual production speed of the line is 49.6 bottles/min.

This is then compared to the theoretical productivity with an infinite buffer. This means the only loss in productivity is from the machine being down so it is the ratio of the up-time to up-time + down-time. This results in a theoretical speed of 64.8 bottles/minute, which is a 34% increase over the modeled/actual production speed with a zero-buffer.

In reality, the size of the buffer should be somewhere in-between. The best way to demonstrate the impact of the buffer size on the theoretical production speed is through a simulation. Figure 14 below, shows a graph of the simulation for the size of the buffer and the resulting production speed. We can see that our edge cases (zero-buffer line) is around our modeled and actual speed and the theoretical infinite buffer production speed of almost 65 bottles/minute is approached at close to 100 bottles in the buffer. The code for this simulation is in the appendix.

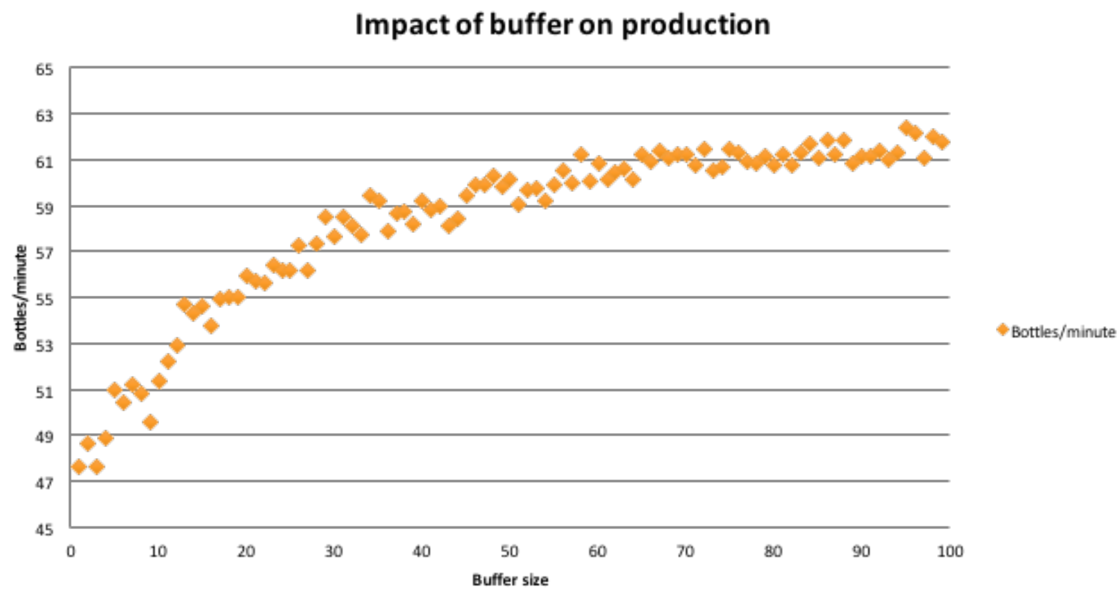

Figure 14: Simulation of inventory buffer sizes with production speed (bottles/minute) using data from one hour time-study

This will indicate that we would not need a buffer of more than 100 bottles (which is just around 1.5 minutes of production time buffer at 75 bottles/minute production speed) in order to approach a much higher production speed. However, these numbers will have to be re-evaluated with the IIoT system, which will provide longer-term study and a more accurate recommendation of the appropriate buffer size. While a longer term time study would be sufficient to calculate a reasonably accurate buffer size, the IIoT system can provide additional data to allow for a changing buffer size and other added buffer functionality.

6.7. Challenges in implementation

As of March 19th, 2017, the PLC and servers have been installed, with a few more weeks required for further integration. This represents a delay of about 2 months as the whole project was supposed to be completed by March 1st. We see the initial hesitation for implementing this system due to the risk to the current system. Even with our approach to avoid connecting into the existing PLCs, we still have to connect into the sensors. The factory has a culture of continuous improvement and a number of other programs that demonstrate their willingness to implement new projects, but a minor organizational barrier in the budget approval process delayed the project. Traditionally most factories would have a financial barrier that is caused by cash flow problems and issues securing bridge financing, but that is not the case with this factory because it its part of Li & Fung, which has the capital for such improvement projects.

7. Recommendations and conclusions

7.1. Thesis summary

This project steps through first understanding the degree of technology adoption in factories through an existing data set (the technical audit), then attempting to expand this understanding through a specifically designed survey (vendor survey), while simultaneously diving deep into a technology implementation project (IIoT). This approach allows for a comprehensive yet detailed understanding that brings about a number of recommendations for Li & Fung and the industry as a whole.

7.2. Understanding supplier capabilities

The reason this project begins with an analytic review of technology implementation in factories is that it is key to begin with a foundation of knowledge about one's supply chain. This information, although far from perfect, gives a number of powerful recommendations.

The technology adoption exploration through the technical audit and vendor survey demonstrates some interesting correlations, especially the correlation between factory performance and technology adoption for a couple technologies (Autospreaders and CAD) in the technical audit. This analysis begins to demonstrate and quantify the impact that these technologies can have on various metrics in the supply chain. These technologies have been around for a significant amount of time and therefore should be well characterized by the factories. By understanding the exact financial benefit, Li & Fung can help factories with more robust business cases for the technology investment. Li & Fung will also be able to more easily make informed decisions about which factories to partner with by predicting the productivity of new suppliers based on the equipment they have.

We also see that the factories respond that they do not see the applicability of many technologies and therefore, since we do believe these technologies are applicable to their factories, they are simply not aware of the applicability of some of these technologies. With the reach and reputation that Li & Fung has, they are in a strong position to help inform and spread knowledge about these technologies. By offering additional services around helping factories implement new technologies they can become the industry leader and make themselves more valuable to their customers.

In addition, we see that there is a correlation with lean programs and technology adoption. This indicates that since there are correlations between lean programs and technology adoption, they must go hand-in-hand. Li & Fung is currently building its service offerings in lean programs, which should be complemented by the service offerings in technology implementation.

When it comes to barriers to adoption, financial and strategic barriers were identified as the key issues. However, this is offset in larger factories which have longer expected ROI periods. All of these show promise to the benefit and impact of implementing technology in factories. These take-aways also demonstrate where efforts should be placed to help factories further adopt technology (e.g., in providing financial lines of credit and sharing technical expertise).

However, we also see the limit to having factories self-report technology adoption. This indicates that Li & Fung should strongly consider expanding the technical audit to avoid factories self-reporting and be able to more accurately detail technology capabilities. Currently the technical audit only asks a few questions about relatively well adopted technologies and therefore Li & Fung should consider expanding the questions to encompass additional technology questions.

7.3. Value of production level data

The IIoT project in the automated bottling factory in Thailand provides further insight into the potential benefit of technology in factories. The system is a relatively low-cost and quick implementation, even despite potential delays. For under $50k for materials, development, implementation, and integration, this project is a small commitment for many factories. In addition, the project went from conceptualization to implementation in under 6 months. This speaks to the power of rapid prototyping and to the Fung Academy's culture of action. The system developed is a low-risk implementation with potential high impact. For example, we see that an inventory buffer, which is optimized through the data from the IIoT system, can increase OEE by as much as 34%. We see again, however, organizational barriers and the necessary budget approval process slightly delaying the start of the project by just over a month.

Li & Fung is also currently piloting an RFID system for tracking bundle flows for sewing lines. The pilot is still collecting data to understand the impact of the system, but it is clear that there is promise in these real-time digital data tracking systems. The better a factory understands its its production lines, including productivity and quality, the better it can make positive changes. More sophisticated data analysis techniques, including machine learning, make the data more valuable. In addition, if Li & Fung can develop the business model where they own the data from all the factories, i.e., the ones they do not own, they will be in an incredibly powerful position to leverage this information at a supplier network and even industry level. They would be able to optimize their own supply chain with all this information of factory, even production line productivity and quality, but also they could use this information to drive changes in the entire industry, either by selling the data or setting standards.

7.4. Automation capabilities

While the LF Beauty factory was semi-automated, there is still a long way to go for automation at a large scale in the cut and sew factories. Some of the cutting edge factories have laser cutters for etching jeans and some factories are exploring other applications. However, I speculate that we are still 5-10 years out before any of the automated equipment is developed that will make a significant impact on the industry. Li & Fung, by continuing to survey its supplier base, can help catalyze the spread of any major break through and should continue to monitor closely the progress of these cutting edge factories. Perhaps a few technology partnerships (different than just strategic partners) could be useful to Li & Fung and to others in the industry to allow for a more rapid development and adoption of these not yet proven technologies. Li & Fung could allow for rapid deployment of pilots of these technologies in factories that are well suited to test and experiment.

7.5. Future work

The most appropriate work to follow is to gather additional detail in factories around technology adoption. The technical audit is a great start, but to expand on the 5 technologies included in the technical audit would provide more information on technology adoption. This would allow for more reliable data to be correlated and therefore have more confidence in the factors that will influence technology adoption. One ideal solution would be some sort of automated data collection system to be put in place that would minimize the dependence on the technical audits. This is essentially a technology solution for understanding technology adoption and usage.

Further work is also promising in the implementation of real-time digital data capture systems in the Thailand facility (as well as other facilities). There is a lot of data that can help with process improvements, but it is not gathered currently. The IIoT project will be monitored carefully to observe what can be learned form it and how it can be rolled out (if successful) to other factories as quickly and comprehensively as possible.

7.6.Conclusion

Technology adoption, even in low-cost sourcing countries, has become relevant and increasingly important to the success of these factories. It is important to continue to monitor the technology adoption to understand the potential benefits as well as the barriers for implementation. From there, it is possible as we have demonstrated, to rapidly develop a low-cost, low-risk and impactful technology solution. Li & Fung is well positioned to a be a leader in manufacturing technology implementation in these factories and can have a strong positive impact on the industry.

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9. Appendix

COEFFICIENTS OF LOGISTIC REGRESSION

	Electronic sewing	Specialized	Whole garment	CNC	Other automation	Conveyor	Robotic arms	Real-time digital data capture	Advanced water tech
(Intercept)	15.9	16.9	0.7	17.1	15.3	17.0	18.9	15.1	17.9
Lean programs	0.7	0.3	1.0	0.2	1.1	0.8	0.4	1.4	1.6
Country Bangladesh	-14.3	-16.9	NA	-16.3	-16.8	-18.3	-21.3	-19.4	-19.3
Country Cambodia	-17.3	-18.1	-3.6	-17.5	-16.9	-18.0	-37.9	-18.7	-19.5
Country China	-15.8	-17.1	-2.7	-16.5	-17.4	-17.7	-19.7	-18.0	-19.7
Country Egypt	0.1	0.3	NA	NA	0.3	1.0	NA	NA	-36.7
Country Indonesia	-15.0	-16.5	-0.1	-16.7	-15.5	-18.3	-39.0	-17.2	-19.9
Country India	-15.5	-18.1	-2.7	-17.4	-17.4	-18.9	-39.2	-18.5	-18.7
Country Jordan	-1.8	-0.2	NA	-0.1	-0.8	0.1	-37.7	-34.8	-38.9
Country Lesotho	0.9	-0.2	NA	0.2	-1.9	1.1	-36.3	-0.9	-0.8
Country Nicaragua	0.7	-0.4	-18.6	-35.0	-34.1	-33.3	-36.7	-32.8	-37.1
Country Portugal	1.0	0.2	NA	-0.2	0.1	-0.3	-19.6	-0.2	NA
Country Sri Lanka	-0.1	-0.3	NA	0.3	-0.8	-16.7	NA	-16.2	-18.9
Country Thailand	-16.2	-17.8	-18.0	-17.3	-17.1	-19.7	-39.6	-19.1	-36.6
Country Turkey	-15.5	-17.0	NA	0.5	NA	1.5	-39.7	-17.9	-17.7
Country Taiwan	-15.7	-0.1	NA	0.5	-17.5	-0.5	NA	-32.8	NA
Country Vietnam	-14.8	-16.1	-2.7	-17.1	-16.4	-17.1	-20.2	-17.8	-20.2
Customer Brand	0.1	-0.1	-0.6	-0.6	1.1	-0.6	0.5	0.1	0.2
Customer Club	-18.2	15.6	-15.4	-18.2	17.0	-17.6	-16.9	-15.0	-16.0
Customer Dep Store	0.1	-1.1	-2.8	0.1	1.5	0.3	0.9	0.3	0.5
Customer e-commerce	0.1	-1.3	0.0	-1.0	-0.5	-1.7	-18.0	0.4	-16.5
Customer Hypermarket	0.7	-0.2	0.5	-0.1	1.6	0.6	0.6	0.3	-0.8
Customer off-price	-1.0	-1.2	-18.3	-1.9	0.8	0.0	3.0	-0.6	-18.3
Customer Specialty	0.0	0.1	0.1	-0.5	1.4	0.0	1.2	0.6	0.4
Median annual turnover	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
In-house design department?	0.3	0.3	-0.7	0.4	0.1	0.8	0.7	0.5	0.0
Fabric platforming capability?	0.1	0.3	-0.4	-0.5	0.6	-0.5	-1.3	0.1	-0.5
Product lifecycle management software?	1.5	0.1	0.1	0.0	-1.1	-0.2	-1.1	0.3	0.4
ROI between 1-2 years	-0.6	0.0	1.8	0.3	-0.2	0.0	-1.2	0.4	-0.8
ROI between 6 mths to 1 year	0.1	0.0	1.9	-0.1	-0.1	-0.4	0.1	-0.2	-0.3
ROI within 6 months	-0.1	-0.1	0.2	0.1	0.5	0.0	-0.4	0.7	-0.5
Passive	0.4	0.5	-1.8	0.6	0.0	0.7	-0.2	0.9	0.2
Promoter	0.7	0.6	0.1	0.7	0.3	1.0	0.5	0.6	0.3

p-values for coefficients of logistic regression

	Electronic sewing	Specialized	Whole garment	CNC	Other automation	Conveyor	Robotic arms	Real-time digital data capture	Advanced water tech
(Intercept)	0.99	1.00	0.69	1.00	0.99	1.00	1.00	0.99	1.00
Lean programs	0.09	0.45	0.11	0.57	0.00	0.03	0.53	0.00	0.00
Country Bangladesh	1.00	1.00	NA	1.00	0.99	1.00	1.00	0.99	1.00
Country Cambodia	0.99	1.00	0.04	1.00	0.99	1.00	1.00	0.99	1.00
Country China	0.99	1.00	0.01	1.00	0.99	1.00	1.00	0.99	1.00
Country Egypt	1.00	1.00	NA	NA	1.00	1.00	NA	NA	1.00
Country Indonesia	1.00	1.00	0.93	1.00	0.99	1.00	1.00	0.99	1.00
Country India	0.99	1.00	0.02	1.00	0.99	1.00	1.00	0.99	1.00
Country Jordan	1.00	1.00	NA	1.00	1.00	1.00	1.00	0.99	1.00
Country Lesotho	1.00	1.00	NA	1.00	1.00	1.00	1.00	1.00	1.00
Country Nicaragua	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99	1.00
Country Portugal	1.00	1.00	NA	1.00	1.00	1.00	1.00	1.00	NA
Country Sri Lanka	1.00	1.00	NA	1.00	1.00	1.00	NA	0.99	1.00
Country Thailand	0.99	1.00	0.99	1.00	0.99	1.00	1.00	0.99	1.00
Country Turkey	0.99	1.00	NA	1.00	NA	1.00	1.00	0.99	1.00
Country Taiwan	0.99	1.00	NA	1.00	0.99	1.00	NA	0.99	NA
Country Vietnam	1.00	1.00	0.11	1.00	0.99	1.00	1.00	0.99	1.00
Customer Brand	0.87	0.84	0.59	0.32	0.13	0.34	0.62	0.90	0.85
Customer Club	0.99	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
Customer Dep Store	0.90	0.14	0.10	0.91	0.07	0.72	0.37	0.75	0.72
Customer e-commerce	0.96	0.24	0.98	0.33	0.73	0.18	1.00	0.79	1.00
Customer Hypermarket	0.47	0.84	0.72	0.94	0.07	0.49	0.59	0.81	0.64
Customer off-price	0.53	0.47	0.99	0.09	0.52	0.98	0.08	0.67	1.00
Customer Specialty	0.99	0.86	0.96	0.41	0.06	0.98	0.24	0.54	0.75
Median annual turnover	0.30	0.91	0.10	0.52	0.49	0.23	0.28	0.89	0.44
In-house design department?	0.34	0.34	0.27	0.14	0.77	0.03	0.23	0.24	1.00
Fabric platforming capability?	0.79	0.32	0.50	0.09	0.08	0.16	0.02	0.86	0.33
Product lifecycle management software?	0.03	0.79	0.90	0.97	0.02	0.70	0.32	0.63	0.60
ROI between 1-2 years	0.25	0.94	0.12	0.49	0.69	0.96	0.17	0.41	0.28
ROI between 6 mths to 1 year	0.90	0.97	0.11	0.81	0.80	0.49	0.92	0.69	0.68
ROI within 6 months	0.80	0.92	0.85	0.91	0.35	0.98	0.65	0.22	0.56
Passive	0.38	0.31	0.11	0.19	0.92	0.22	0.81	0.15	0.81
Promoter	0.07	0.12	0.87	0.04	0.47	0.02	0.41	0.22	0.65

Performance metrics used

Metrics Area	Metric Name
Delivery	FOB Shipped On-time (by OSD)
	PO Shipped On-time (by OSD)
	Quantity Shipped On-time (by OSD)
	FOB Impact from Delay (by OSD)
	Quantity Impact from Delay (by OSD)
	FOB Shipped On-time (by RSD)
	PO Shipped On-time (by RSD)
	Quantity Shipped On-time (by RSD)
	FOB Impact from Delay (by RSD)
	Quantity Impact from Delay (by RSD)
Production Accuracy	Short Ship Rate by Quantity
	Short Ship Rate by Shipment Item
	Over Ship Rate by Quantity
	Over Ship Rate by Shipment Item
Compliance - Social and Ethical Compliance	Social & Ethical Compliance
Quality	1st Final Inspection Pass Rate
	Final Re-inspection Rate
	Final Defect Rate
	In-line Defect Rate
	Inline to Final Ratio
	Maintenance Factor (Non-Final to Overall Inspection Ratio)
Documentation	Document Resubmission Rate

Python code for simulation of buffer sizes

```
total = 0
number_of_simulations = 1
buffer_sizes = range(1,100)

for x in buffer_sizes:
  mttr1 = 22 # seconds
  mttr2 = 22 # seconds
  mttr3 = 22 # seconds
  mttf1 = 141 # seconds
  mttf2 = 141 # seconds
  mttf3 = 141 # seconds
  production_speed = 3*[75] # bottles per minute

  mttrR = [mttr1, mttr2, mttr3]
  mttr = [mttr1, mttr2, mttr3]
  mttf = [mttf1, mttf2, mttf3]
  machine_up = 3*[1] #machines all start working
  maxbuffersize = [np.inf,x,x,np.inf]
  buffersize = [np.inf,0,0,0]
  simulationseconds = 86400 # seconds

  while simulationseconds > 0:
    simulationseconds-=1 # reduce seconds
    for index in range(3):

      if machine_up[index]==1 and buffersize[index]>0 and buffersize[index+1] <=
maxbuffersize[index+1]:
        # if all conditions met, then 1second*productionspeed number of bottles gets
moved over
        buffersize[index]-=(production_speed[index]/60) #
(bottles/1minute)/(60seconds/1minute)
        buffersize[index+1]+=(production_speed[index]/60) #
(bottles/1minute)/(60seconds/1minute)

      if machine_up[index]==0: # if down, try to fix it
        if mttr[index]==0: #if mttr seconds passed, its now fixed and reset number
          machine_up[index]=1
          mttr[index]=mttrR[index]
        else:
          mttr[index]-=1
      else:
```

```
            if np.random.rand()<=(1/mttf[index]):
                machine_up[index]=0
    print(x,buffersize[3]/86400*60)
```

Screenshot of page in SurveyMonkey survey

* 25. Please share your company's involvement and adoption of the below tools and technologies.

	Not applicable	No decision yet	Already implemented	Plan to implement
Electronic sewing machines	○	○	○	○
Specialized sewing machines (e.g., auto placket, auto pocket, auto collar)	○	○	○	○
Whole-garment knitting machines	○	○	○	○
Computer controlled machines (e.g., auto cutters, laser etcher, auto embroidery)	○	○	○	○
Other automated equipment (e.g., auto spreader, auto steamer/presser)	○	○	○	○
Conveyor system (e.g., overhead conveyor or conveyor belt)	○	○	○	○
Robotic arms (e.g., robotic spraying, robotic sanding, pick and place robots)	○	○	○	○
Real-time digital data capture (e.g., RFID, in-line tablet to enter data directly, energy monitoring sensors)	○	○	○	○
Advanced water tech (e.g., "waterless" washing/dyeing, reverse osmosis for water recycling)	○	○	○	○

* 26. In which technology areas could you use help?

- ☐ Electronic sewing machines
- ☐ Specialized sewing machines
- ☐ Whole-garment knitting machines
- ☐ Computer controlled machines
- ☐ Other automated equipment
- ☐ Conveyor system
- ☐ Robotic arms
- ☐ Real-time digital data capture
- ☐ Advanced water tech

* 27. What are the challenges in implementing new technology projects?

- ☐ Upfront cost
- ☐ Additional expertise needed to implement
- ☐ Recurring maintenance cost
- ☐ Training resources required
- ☐ Interruption to on-going production for installation
- ☐ The right technology does not exist
- ☐ Market and economic uncertainty
- ☐ Agreement among groups/departments in company
- ☐ Company culture

Other