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WORK INTERRUPTION: THE MODERATE EFFECT OF WORKLOAD AND QUEUE LENGTH IN THE MANUFACTURING INDUSTRY

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ABSTRACT

This paper explores the relationship between process interruption, workload, queue length, and worker productivity. Based on the data from the loading process in a manufacturing enterprise, the Cox proportional hazards rate model was utilized for empirical analysis. By defining two types of stochastic process interruptions (type I and type II), our empirical results found that process interruption harms worker productivity for 30 minutes after the end of the interruption. It was also concluded that the queue length in the loading process strengthens the negative relationship between the two types of interruptions and worker productivity. However, it is a different story for the moderate effect of workload; the negative effect of the type I interruption on worker productivity is stronger under a low workload, while it gets stronger for the type II interruption under a high workload. Our empirical findings firstly validated the strengthened effect of queue length on the relationship between process interruption and worker productivity. Additionally, we also found the different roles of workload on the relationship between different types of interruptions and worker productivity.

Contribution/Originality: This study is one of the very few studies which explore the moderator role of workload and queue length on the relationship between work interruption and productivity in the manufacturing industry.

1. INTRODUCTION

In the manufacturing industry, operational performance is often affected by many kinds of variability factors. Process interruption is one of the common factors of variability, which plays an important role in an enterprise's operational performance. Generally, process interruption causes an increased cost of the production system and has a negative effect on the system's operational performance. The phenomenon that production variability may cause an increased process cost is widely recognized (Lee & Billington, 1993; Novák & Popesko, 2014). Hopp and Spearman (2011) believe that increasing variability always deteriorates the production system's performance. Once interruption occurs in the manufacturing system, the subsequent periods will be affected from the current workstation to the whole production system.

It is well known that human plays a key role in the manufacturing industry and their behaviors fluctuate under the occurrence of some operational factors. Former scholars have found that workers' learning (KC, Staats, & Gino, 2013), the interaction between workers and their customers (Buell, Kim, & Tsay, 2016) and task selection (Freeman, Savva, & Scholtes, 2016; KC, Staats, Kouchaki, & Gino, 2020) can all play such a role. Generally, modeling human behaviors is very difficult, therefore, we must explore factors that have an important impact on human behaviors. In the current era of big data, data recording and acquisition is relatively simple, and rich data helps us identify factors that influence employee behavior and the performance of the operation system.

Regarding the research on interruption, some studies explored how interruption affects worker productivity (Cai et al., 2018; Di Pasquale, Fruggiero, Iannone, & Miranda, 2017; Froehle & White, 2014; Pang & Whitt, 2009; Sanderson & Grundgeiger, 2015; Trougakos, Beal, Green, & Weiss, 2008). However, some other factors may also affect worker productivity by changing their behaviors, such as workload (Dietz, 2011; KC & Terwiesch, 2009; Tan & Netessine, 2014) and the queue waiting length (Delasay et al., 2016; Wang & Zhou, 2017). The truth is that all the factors, such as interruption, workload and queue waiting length, can affect worker behavior and further cause a change in their productivity. To the best of our knowledge, there is no comprehensive discussion on this issue that contains the factors of interruption, workload, queue waiting length and operational performance simultaneously. When an interruption occurs, it can impact employee productivity by changing their operation behaviors. At the same time, the relationship between interruption and employee productivity may also be affected by the environment factors including workload and queue waiting length. Currently, this question has not received sufficient attention from scholars in the empirical evidence.

In this paper, we investigate how interruption, workload and queue waiting length affect worker operational performance in the manufacturing industry. We studied a loading process of product testing in a manufacturing enterprise. Based on field data, this paper explored three questions. The first is how different stochastic interruptions (type I and type II) affect worker productivity; the second question explores the moderate function of workload levels on the relationship between each type of interruption and worker productivity; and third, the moderate role of queue waiting length on the relationship between each type of the interruption and worker productivity is explored.

This paper is organized as follows: section two provides the literature review and corresponding hypotheses; section three describes the research background and data; the empirical analysis is executed in section four; and in section five we conclude and discuss the management implications of the main findings.

2. LITERATURE REVIEW AND HYPOTHESES

In manufacturing, variability is always the enemy of performance of a production system (Wang & Hu, 2018; Wu, Zhou, & Zhao, 2016), and stochastic interruption, which frequently causes process variability, is ubiquitous in the production line. Therefore, exploring the effect of process interruption on worker productivity is meaningful to the manufacturing industry. Research on interruption has received attention from scholars for a long time. Generally speaking, an interruption is anything that breaks into a user's current activity and demands a person's attention to shift to another activity (Kolbeinsson, Thorvald, & Lindblom, 2017). In practice, there are many types of event that play such a role and disrupt the current primary task. Based on a relatively integrated perspective of interruption, Jett and George (2003) divided interruptions into four categories. In general, we can divide process interruption into two categories in the production environment: scheduled interruptions and stochastic interruptions. The occurrence of scheduled interruptions is relatively fixed and contains mainly daily rests and meals during the production shift. However, the causes of stochastic interruptions come from a wider range of sources. Machine downtime, rework, product failure and other random events can all result in stochastic interruptions during the manufacturing process. The taxonomy of interruptions in the manufacturing industry is shown in Figure 1. In this paper, we focused on the stochastic interruptions and explored their effects on worker operational performance.

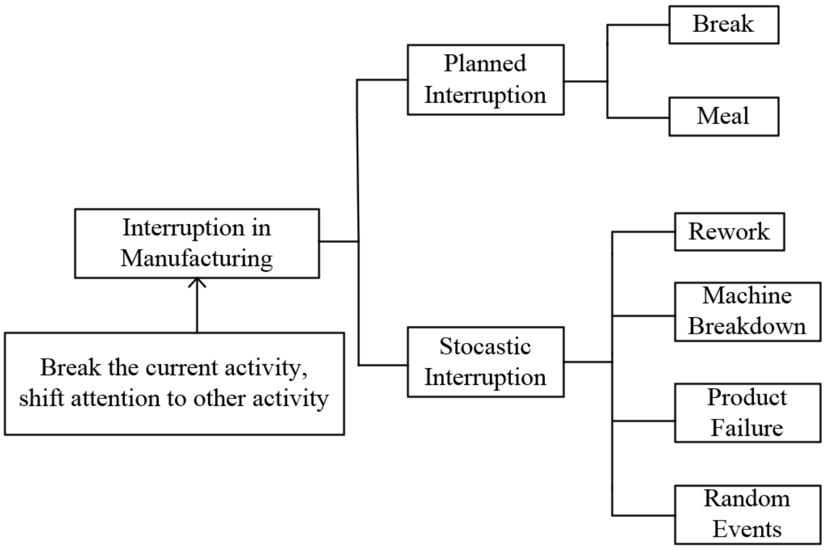

Figure 1. The taxonomy of interruptions in the manufacturing industry.

Many previous studies have examined the relationship between process interruption and worker productivity. Once the production or service processes are interrupted, employees can get a temporary break until the interruption is over. Whether the occurrence of interruptions improve or hinder the productivity of employees is still controversial, though there are a few studies that hold the view that interruptions can promote employee performance (Csikszentmihalyi, 2000; Kim, Park, & Headrick, 2018; Pendem, Green, Staats, & Gino, 2016; Trougakos, Hideg, Cheng, & Beal, 2014), and their findings are usually established under a relatively narrow condition, especially the break interruptions. For instance, Csikszentmihalyi (2000) thinks that breaks caused by interruptions improve workers' emotional well-being and bring organizational benefits if they participate in fulfilling and enjoyable activities during the breaks. Pendem et al. (2016) explored the microstructure of work and three types of break interruptions in a tomato-harvesting process: expected breaks, unexpected breaks that need people's focus, and unexpected breaks that do not need people's focus. They concluded that only the unexpected breaks that need people's focus generate immediate post-break productivity increases. However, the other two types of break interruptions both harmed harvester performance. Those research studies demonstrated that the positive effects of interruptions exist only in a few specific conditions. Hence, the negative function of process interruptions on worker productivity is more popular (Cai et al., 2018; Froehle & White, 2014; Spira & Feintuch, 2005).

Generally, interruptions have a negative effect on operational performance because of distracted attention and difficult work transition (Altmann & Trafton, 2007), time pressure (Leroy & Glomb, 2018), depressed mood (Cai et al., 2018; Ockenfels et al., 2015) and reduced proficiency or forgetfulness (Froehle & White, 2014; Teyarachakul et al., 2011). First, interruptions can affect workers' mental cognition and trigger the anticipated time pressure of finishing the task. Leroy and Glomb (2018) revealed that when people anticipate resuming their interrupted work under time pressure, it is difficult to switch their attention to the interrupting task, leading to attention residue and low performance. Second, interruptions that disrupt the primary task can also result in a depressed mood. Cai et al. (2018) studied the impact of machine interruptions on subsequent output based on a treatment effect model. This study found that machine interruptions triggered negative emotional reactions and led to a 3% drop in employee output the following day. Third, disrupted attention may contribute to feelings of boredom with the current task (Fisher, 2018). The distraction, caused by interruption, may be difficult to transform. Finally, worker productivity experienced a drop period because the necessary time is required for the reduced proficiency to return to a normal level (Froehle & White, 2014). After an interruption, workers need to spend some time to familiarize themselves with the previous work before returning to the pre-interruption production level. Figure 2 shows four factors from the above research which may cause a deterioration in performance after an interruption: distracted attention, time pressure, depressed mood and reduced proficiency. Hence, we propose Hypothesis 1 as follows:

Hypothesis 1: Process interruption deteriorates worker productivity after the end of an interruption.

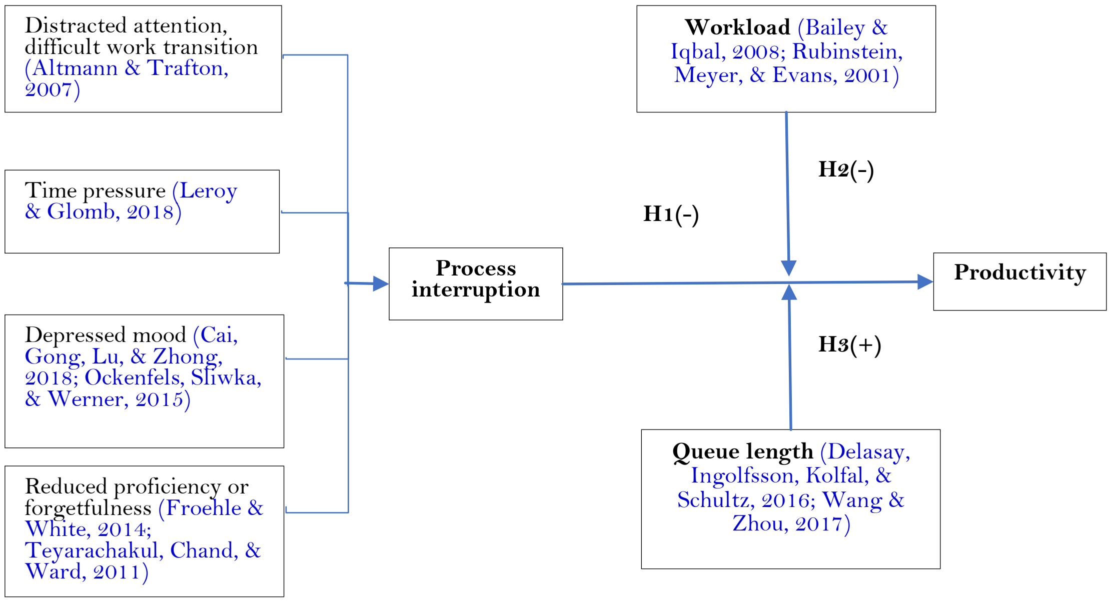

Figure 2. Research framework and hypotheses.

Workload is an important factor in the production system and impacts workers' operational behavior. Some studies have found a positive effect of workload on worker performance in manufacturing and service sections (Berry Jaeker & Tucker, 2016; KC & Terwiesch, 2009; Schultz, McClain, & Thomas, 2003). To the best of our knowledge, most studies concentrated on the impact of workload levels on worker performance. However, we are interested in whether workload affects the relationship between process interruption and worker productivity. Speier, Vessey, and Valacich (2003) provided evidence that interruptions have a larger negative effect on more complex tasks than on simpler tasks. Rubinstein et al. (2001) and Bailey and Iqbal (2008) concluded that when ongoing task interruptions occur at lower mental workload levels, the cost of the interruptions is reduced. Similarly, if an interruption caused by a delivery notification occurs at a low workload level, the cost of the interruption will also decrease (Kolbeinsson, 2016). The above analysis proposes evidence that a lower workload is more beneficial for the operational performance of the system when an interruption occurs. Additionally, recent research by Pendem et al. (2016) found that the higher workload of tomato harvesters increased the negative effects of unexpected breaks requiring an active response on their productivity. After this type of interruption is over, the cognitive setup associated with restarting the focal task placed a burden on cognitive resources. When the cognitive resources are scarce because of employees' fatigue and depletion caused by a higher workload level, they will be motivated to conserve (Pendem et al., 2016). Therefore, we believe that a lower workload is likely to mitigate the interruptions' adverse functions.

Based on Hypothesis 1, that interruption has a negative impact on worker productivity after the interruption is over, we assume that workload plays a moderated role in the effect of interruption on worker productivity. Therefore, Hypothesis 2 is proposed as follows:

Hypothesis 2: Workload moderates the relationship between process interruption and worker productivity, such that the negative effect of interruption on worker productivity is stronger under higher workload levels than under low workload levels.

In a production line, queue length faced by employees may affect their operation behaviors. Many research models based on queue theory and interruption theory have explored the impact of interruptions on the queue system (Krishnamoorthy, Pramod, & Chakravarthy, 2014; Kumar, Rukmani, Thanikachalam, & Kanakasabapathi, 2018). However, there are no studies that have explored how interruptions influence worker performance under different queue lengths. Just like the *Workload* variable, the number of products waiting in the queue may generate psychological and emotional pressure for employees when a stochastic interruption happens (Delasay et al., 2016; Wang & Zhou, 2017). As the number of products waiting in the queue becomes larger, employees may experience greater pressure. Hence, a long queue may increase the cost of interruptions and decrease worker productivity. KC and Terwiesch (2009) provided evidence that workers have lower service time with fewer tasks in the queue. Deterioration of productivity may result from two aspects caused by longer queue length. First, more products waiting in a queue can cause a higher psychological burden. This undoubtedly makes the negative effect of the interruption worse. Additionally, a crowded queue also breaks the normal work rhythm and work rhythm chaos can cause frustration for employees. Therefore, the negative impact of interruptions on worker productivity may be stronger under a larger queue length. Based on this, Hypothesis 3 is proposed as follows:

Hypothesis 3: Queue length moderates the relationship between process interruption and worker productivity, such that the negative effect of interruption on worker productivity is stronger under larger queue length than under shorter queue length.

3. BACKGROUND AND DATA

In this section, we describe the working background of the production process (loading process) in detail. The data collected was used to verify the above assumptions.

3.1. Manufacturing Background

Our research selected an assembly line in a manufacturing company to test our hypotheses. The assembly line consists of six different processes. We mainly focused on the loading process and regard the subsequent five procedures as a whole process. The loading process is the first procedure in this assembly line, which has a test employee and a test machine with two jacks. Once the product arrives at the assembly line, the employee inserts the products into the test machine alternately. The product test procedure is conducted according to the first in, first out rule. The time that the product is tested in the machine is generally very short. Under common circumstances, the output of the employee in a day shift exceeds 4,000 products. As shown in Figure 3, when the product arrives at the loading process, the testing procedure initiates. Since the time taken to remove the product from the machine is negligible compared to the test time, we do not consider the precise time at which employees insert and remove the product, and we reasonably take the time difference between two adjacent products into the loading process as the test time of the previous product. When the product finishes the test procedure, it waits in the queue before being sent to the next process. We divided the loading process of the product into two time periods – testing and waiting. The enterprise's production system records the time point when the product enters the loading process and the sub process, through which we can calculate the waiting time of each product.

As the loading process is the first step in each assembly line, the interruption that occurs during the loading process mainly results from two aspects. The first type of interruption happens during the testing procedure of the loading process (interruption type I), where factors such as machine breakdown, product failure and the temporary departure of workers can all lead to this type of interruption. Thus, the primary consequence of type I interruptions is the elongated testing time of a certain product. The second interruption happens in the subsequent processes after the loading (interruption type II), where the occurrence of random events from the second to the sixth procedure will lead to this type of interruption. Obviously, when a type II interruption occurs, the product will wait longer in the buffer between the loading process and the second procedure.

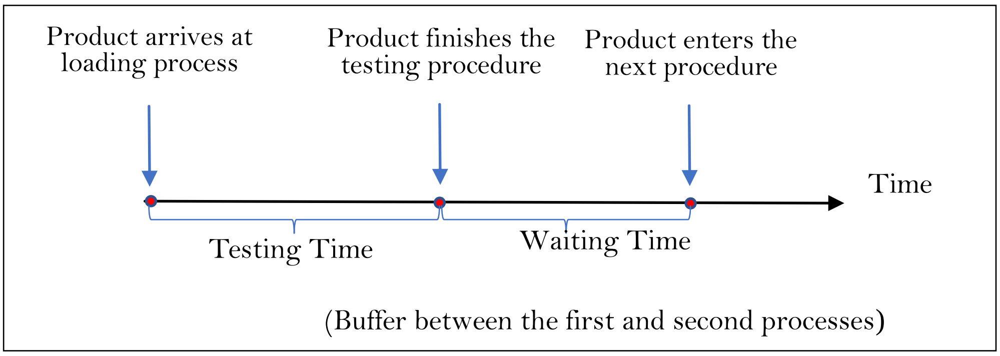

Figure 3. The loading process of the assembly line.

The difference between the two types of interruption is that the occurrence of the interruption of type I only extends the testing time of the product without affecting the waiting time in the buffer between the first and second procedures. This paper explores the impact of the above two types of interruptions on the productivity of the loading process. Additionally, during the work shift, employees take breaks and eat at fixed times, and one shift will be divided into multiple consecutive work phases according to the break and eating schedule.

3.2. Data

3.2.1. Data Selection and Processing

Our study selected the data from the assembly line for 54 day shifts from September 2019 to December 2019. Through processing the data, we removed the product test records that were incomplete due to recording errors and missing information. Based on the break and eating schedule, we obtained five consecutive work stages from each work shift. The fifth work stage of each day shift has high variability than the other four stages because this stage is the last work phase of a day shift and shift exchange among employees often occurs at this point. According to the on-site investigation, the data recorded in this stage is disordered from time to time, which may induce bias in our analysis; therefore, data from the fifth stage was excluded. Additionally, this study retained the test records of 232,000 products.

The most critical part of the data processing was the definition of interruptions. The data recorded in the loading process of the enterprise only records the time point at which the product arrives at the loading process and the next process and does not record the times or reasons for the interruptions. Therefore, we are unable to accurately determine the exact times and reasons for the interruptions. Fortunately, the loading test procedure is simple with an average test time of less than seven seconds. We can reasonably define the interruption events based on the property of the testing procedure. This paper defines two types of interruptions that occurred during the testing procedure of the loading process and the subsequent assembly processes according to the 3σ principle. First, for the testing procedure, we adopted the time difference of two adjacent products when they arrived at the loading process as the actual test time of the previous product. We calculated the mean to be 6.84 seconds with a standard deviation of 12.25. According to the 3σ principle, we defined the product test records with a product test time greater than $\mu+3\sigma$ as interruption type I of the testing procedure of the loading process, i.e., when the difference between the arrival time of two adjacent products at the loading process is greater than 43.6 seconds, interruption type I happens. Second, for interruptions during the subsequent process, we defined the interruptions as type II according to the waiting time of the product in the loading process. Intuitively, the long waiting time of a product during the loading process indicates that the subsequent processes have been interrupted, which means the product stays in the assembly queue for a relatively long time. Similarly, we calculated the average waiting time during the loading process, which is 116.85 seconds, with a standard deviation of 68.77. According to the 3σ principle, we defined the product test record whose queue waiting time in the loading process is greater than

$\mu+3\sigma$ as interruption type II, i.e., when the queue waiting time of a product is greater than 322.9 seconds, interruption type II occurs.

3.2.2. Variables

3.2.2.1. Dependent Variable

$\lambda_{ij}(t)$: The hazard rate of the time that a product stays in the loading process is an efficiency indicator of the assembly line. The detail of the hazard rate is shown in section 4.1 (model selection).

3.2.2.2. Explanatory Variables

Interruption type ($\text{int}1_{ijt}$ & $\text{int}2_{ijt}$): Previous studies have shown that the impact of interruptions on operational performance after they occur lasts no more than half an hour (DeJarnette, 2017; Lu, Heching, & Olivares, 2014). Therefore, a time interval of 30 minutes after an interruption was selected to study the impact of interruptions on worker productivity. $\text{int}1_{ijt}$ indicates that the j th product of the i th shift tested at time t is located at the 30-minute time interval after a type I interruption . Similarly, $\text{int}2_{ijt}$ indicates that the j th product of the i th shift tested at time t falls into the 30-minute time interval after the occurrence of a type II interruption .

$workload_{ijt}$: The cumulative number of products that have been finished up to the current moment t for the j th product from the beginning of the i th shift.

$queue_{ijt}$: The number of products waiting in the queue in the loading process (the buffer between the loading process and the second process) when the j th product of the i th shift is testing at time t.

3.2.2.3. Control Variable

Based on the availability of data from selected manufacturing environments, we controlled the following factors.

$stage_{ijk}$: A complete day shift was divided into four consecutive work stages according to breaks and mealtimes. To control the impact of different stages in our model, we defined a set of dummy variables: $stage_{ijk}=1$ to indicate that the j th product of the i th shift at time t belongs to the k th stage, otherwise $stage_{ijk}=0$.

Frequency of interruption: A higher frequency of interruption indicates that the system has a higher variability. Therefore, the variables $\text{int}1\_fre_{it}$ and $\text{int}2\_fre_{it}$ indicate the number of interruptions of both type I and II from the beginning of the i th shift to the current moment t , respectively, which were employed to control for the variability factors. Table 1 provides the descriptive statistics of our variables.

Table 1. Descriptive statistics for our variables.

Variable	Mean	SD	Min.	Max.	1	2	3	4	5	6
1. *int1*	0.80	0.4	0	1	1					
2. *int2*	0.19	0.4	0	1	0.08	1				
3. *workload*	2184.8	1326.21	1	5206	0.01	-0.02	1			
4. *queue*	17.75	10.87	0	127	0.13	0.22	-0.06	1		
5. *int1_fre*	20.53	17.23	0	127	0.21	0.06	0.64	0.11	1	
6. *int2_fre*	3.86	6.19	0	53	0.08	0.25	0.23	0.26	0.47	1

4. EMPIRICAL FINDINGS

4.1. Model Selection

The manufacturing environment selected in this paper has its own unique characteristics. We did not measure the production efficiency of employees by using traditional performance indicators, such as processing time and output rate of the product (KC & Terwiesch, 2009; Staats & Gino, 2012). For example, factors that affect assembly line performance can fluctuate greatly throughout the work shift. Random events are likely to result in increased variability in the assembly line, and it is difficult to measure the production efficiency of employees using only product processing time, output rate and other traditional performance indicators. Hence, we adopted the Cox proportional hazard rate model, which can estimate the hazard rate dynamically (Lu, Musalem, Olivares, & Schilkrut, 2013), to analyze the data. In this paper, the hazard rate corresponds to the failure rate of the loading process completed at the time t under the condition that loading has not been completed until time t.

We know that T is the duration that a product stays in the loading process and the hazard rate is calculated as a function of time t: $\lambda(t)=\lim_{\Delta\to 0}\frac{P(t\le T<t+\Delta)}{P(t\le T)}$. The advantage of modeling productivity as hazard rates can allow productivity to fluctuate during the selected manufacturing environment and offers the opportunity to study the impact of time-varying factors, such as interruptions, queue length and workload on operational performance.

$$\lambda_{ij}(t)=\lambda_0\left(t_{ijt}^{'}\right)e^{\beta X_{ijt}} \qquad (1)$$

Equation 1 shows the hazard rate $\lambda_{ij}(t)$ for the product j at time t, which is located on the loading process of the work shift i; $t_{ijt}^{'}$ represents the cumulative time that the product j has stayed on the loading process of work shift i up to time t; $\lambda_0(g)$ is the baseline hazard rate function, which is estimated by the non-parametric method; X_{ijt} contains the explanatory variables and control variables; and β represents the coefficients of X_{ijt}. As per (Lu et al., 2013), the maximizing likelihood estimates were utilized to estimate our Equation 1.

4.2. Empirical Findings

According to our assembly line data, the average time of the loading process is approximately two minutes. Correspondingly, we discretized the product records into one-minute intervals based on each work shift. The coefficients of Models 1 to 4 were estimated by the Cox proportional hazard model and are shown in Table 2.

Table 2. Regression conclusions of Models 1 to 4.

	Model 1	Model 2	Model 3	Model 4
$queue$	-0.112821***	-0.112854***	-0.169390***	-0.169227***
	(0.000)	(0.000)	(0.001)	(0.001)
$workload$	0.000133***	0.000150***	0.000158***	0.000152***
	(0.000)	(0.000)	(0.000)	(0.000)
$int1\_fre$	-0.017077***	-0.016771***	-0.017460***	-0.017461***
	(0.000)	(0.000)	(0.000)	(0.000)
$int2\_fre$	-0.017507***	-0.017642***	-0.016708***	-0.016729***
	(0.001)	(0.001)	(0.001)	(0.001)
$int1$	-0.080743***	-0.026204**	-0.908094***	-0.893202***
	(0.007)	(0.011)	(0.014)	(0.017)
$int2$	-0.272624***	-0.371787***	-0.839928***	-0.958703***
	(0.006)	(0.012)	(0.012)	(0.017)
$workload \times int1$		-0.000035***		-0.000006
		(0.000)		(0.000)
$workload \times int2$		0.000054***		0.000061***
		(0.000)		(0.000)
$queue \times int1$			0.053125***	0.052807***
			(0.001)	(0.001)
$queue \times int2$			0.028844***	0.029241***
			(0.001)	(0.001)
$stage1$	-0.089828***	-0.087939***	-0.006701	-0.008306
	(0.018)	(0.018)	(0.018)	(0.018)
$stage2$	0.048038***	0.053596***	0.109843***	0.115787***
	(0.013)	(0.013)	(0.013)	(0.013)
$stage3$	0.053823***	0.053057***	0.078215***	0.077326***
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	580,196	580,196	580,196	580,196
Lag length	-2151927.5	-2151866.1	-2147555.9	-2147498.9

Notes: Robust standard errors in brackets *** p < 0.01, ** p < 0.05, * p < 0.1.

As seen in Table 2, our basic model (Model 1) includes the explanatory and control variables (the 30-minute periods after type I interruptions ($int1$) and the 30-minute periods after type II interruptions ($int2$)), the waiting product magnitude in the queue ($queue$), workers' workload ($workload$), the frequency of the two types of interruption ($int1\_fre$ and $int2\_fre$) and work stages ($stage$).

The results from Model 1 demonstrate that both type I and type II interruptions have a negative effect on workers' productivity after their occurrence. The coefficients of $int1$ and $int2$ are -0.081 and -0.273, respectively. This means that 30 minutes of worker productivity is $1 - e^{-0.081} = 8\%$ and $1 - e^{-0.273} = 24\%$ lower than other periods of a work shift, respectively, when interruptions during the loading process testing procedure and further interruptions after the loading process occur. The deteriorated performance may result from workers' reduced proficiency or disturbed work rhythm. Empirical results from the manufacturing environment support the viewpoint that interruptions harm worker productivity after their occurrence, hence Hypothesis 1 is supported.

Coefficients of workload are significantly positive at a 99% confidence level. The positive coefficient indicates that the number of products finished from the beginning of this shift to the current moment improved worker productivity. This shows that worker productivity during the loading process increased by $e^{0.000133} - 1 = 0.01\%$ compared with the last product. This conclusion may result from more learning opportunities to improve their proficiency under a larger workload.

As for the variable of product magnitude waiting in the queue, the negative regression coefficient indicates that the more products waiting in the loading process, the lower the workers' productivity. In this manufacturing environment, loading is the first process of the assembly line. Generally, once the number of products waiting in the queue increases, employees who are working on the loading process will slow down the current work speed accordingly to avoid product congestion. We determined that worker productivity decreases by $1 - e^{-0.113} = 11\%$ on average if the queue for the loading process increased by one more product. Model 1 provides the regression coefficients of control variables. It is obvious that the interruption frequency of both type I and type II interruptions have a negative impact on worker productivity. Generally, more interruptions on the production line can cause larger process variability and the work rhythm of employees is frequently disrupted. Therefore, it is not difficult to understand that frequent interruptions worsen operational performance. Results from Model 1 also show that worker productivity has a significant difference among different work stages.

Model 2 extends Model 1 by involving the interaction terms of accumulated workload and the two types of interruptions. The regression coefficients of Model 2 are consistent with Model 1 in addition to the newly added interaction terms. The results of interaction terms $workload \times \text{int}1$ and $workload \times \text{int}2$ have significant negative and positive coefficients, respectively. This means the moderate function of workload on the effect of interruptions on worker productivity differs for each interruption type. Our regression results demonstrate that the negative effect of loading interruptions on worker productivity is stronger under a low workload and the negative effect of subsequent interruptions after the loading process on worker productivity is stronger under a high workload. Our conclusions partially support Hypothesis 2. The inconsistency between the empirical results and the hypothesis may stem from the following two aspects. On one hand, for interruption type I, it happens in the testing procedure of the loading process and has a direct relationship with the employees at the loading location. When the accumulated product number is low, employees may not have enough work proficiency to deal with the negative impact of stochastic interruptions. Hence, negative impact of interruptions becomes stronger under a lower workload level. On the other hand, for interruption type II, the occurrence of this type of interruption happens during the subsequent processes of loading and is not caused by the loading process. Employees' physical and emotional reactions for interruption events may dominate the effects. When the workload is high, employees have experienced a long working time. Boredom and physical fatigue are likely to strengthen the negative effects of interruptions under a higher workload level.

Like Model 2, Model 3 explored the moderated function of product magnitude in the waiting queue on the effect of the above two types of interruptions on worker productivity. The regression coefficients from Model 3 are consistent with Model 1 except the interaction terms between interruptions and the product magnitude in the waiting queue. The coefficients of interaction terms $queue \times \text{int}1$ and $queue \times \text{int}2$ are both significantly positive. Our empirical results concluded that both of the negative effects of loading interruptions and interruptions after the loading process on worker productivity are stronger when more products are waiting in the queue. Therefore, hypothesis 3 is supported by our empirical data.

4.3. Robustness Checks

To test the robustness of our analysis results in Table 2, we implemented the following tests. First, we included all the explanatory variables, control variables and interaction terms into Model 4. All the coefficients of those variables are consistent with Models 1 to 3. The integral Model 4 provides evidence that the empirical results of Models 1 to 3 are relatively robust. Additionally, we divided the 30 minutes after interruptions happened into three equal intervals of ten minutes. This processing helped us to validate whether worker productivity had a significant difference among 30 minutes after interruptions happened. The regression results are shown in Table 3. We found that all coefficients of the variables were consistent with Model 1, except the virtual variable, which represents the 30 minutes after interruptions happened. Considering these six variables, the coefficients of $int1\_10mins$, $int1\_20mins$, $int2\_10mins$, $int2\_20mins$ and $int2\_30mins$ are negative, which demonstrates that interruptions deteriorate worker productivity. Though the coefficient of $int1\_30mins$ is positive, its magnitude is smaller than the coefficient of $int1\_20mins$ (0.084 < 0.224). Hence, our empirical analysis is robust.

Table 3. Regression conclusions of Model 5.

Model 5			
Variables	Coefficients	Variables	Coefficients
$queue$	-0.113885***	$int1\_30mins$	0.083969***
	(0.000)		(0.010)
$workload$	0.000161***	$int2\_10mins$	-0.569644***
	(0.000)		(0.010)
$int1\_fre$	-0.017940***	$int2\_20mins$	-0.140075***
	(0.000)		(0.010)
$int2\_fre$	-0.014589***	$int2\_30mins$	-0.086692***
	(0.001)		(0.009)
$int1$	-0.080743***	$stage1$	-0.011752
	(0.007)		(0.018)
$int2$	-0.272624***	$stage2$	0.090994***
	(0.006)		(0.013)
$int1\_10mins$	-0.035019***	$stage3$	0.090572***
	(0.007)		(0.009)
$int1\_20mins$	-0.223837***	Observations	580,196
	(0.008)	Lag length	-2150426

Notes: Robust standard errors in brackets *** p < 0.01, ** p < 0.05, * p < 0.1.

5. CONCLUSION

In this paper, we explored two critical questions. First, we defined two types of interruptions and employed data from a loading process in the manufacturing industry to explore the effect of process interruptions on worker productivity. Second, we studied the moderation role of workload and queue length on the negative relationship between process interruptions and worker productivity. No matter the loading interruption (interruption type I) or the subsequent interruptions after the loading process (interruption type II), empirical findings showed that worker productivity deteriorates after interruptions occur. Additionally, we concluded that queue length in the loading process strengthens the negative relationship between both types of interruption and worker productivity. This means both of the negative effects of loading interruptions and subsequent interruptions after the loading process on worker productivity are stronger when more products are waiting in the queue. The moderation role of workload makes little difference. The negative effect of loading interruptions on worker productivity is stronger under a low workload and the negative effect of subsequent interruptions after the loading process on worker productivity is stronger under a high workload.

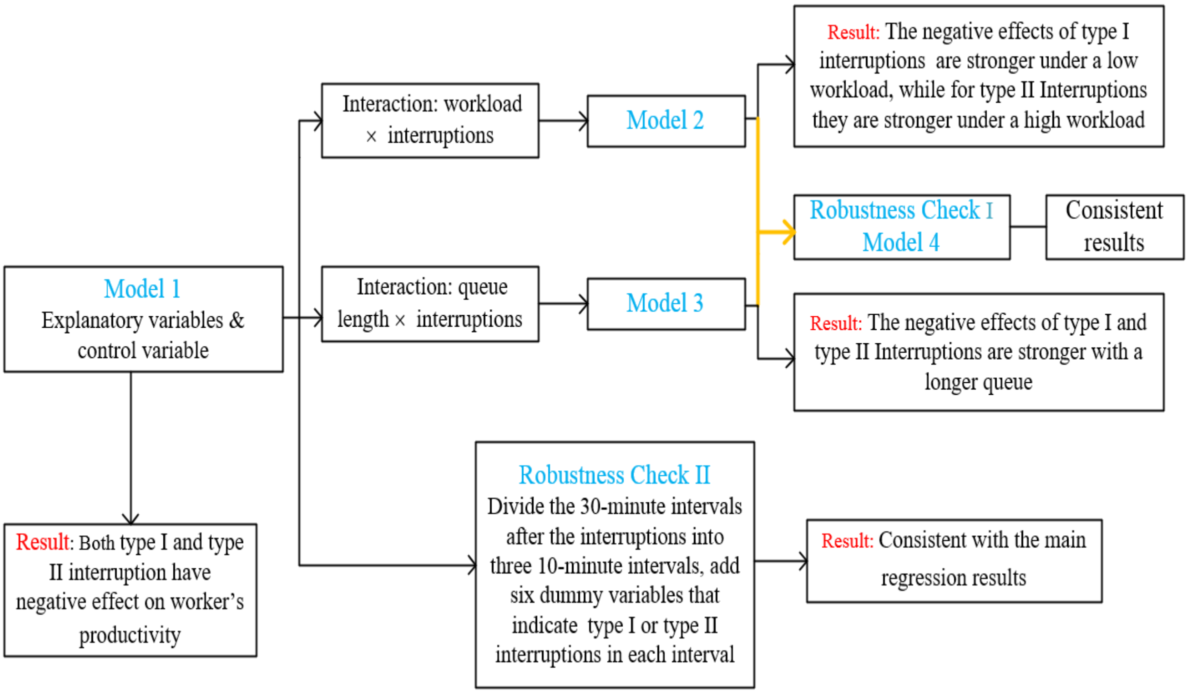

Figure 4. The logic of the model development, the robustness check and their corresponding results.

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