Quality insights: impact of cognitive load on the manufacturing cost of quality

Sharon C. Bommer*

Wright State University,
USA
Email: bommer.2@wright.edu
*Corresponding author

Adedeji B. Badiru

Air Force Institute of Technology,
USA
Email: adedeji.badiru@afit.edu

Abstract: Quality is a multidimensional characteristic of a product. As such, the various factors that impinge on quality must be taken into account when designing new products or managing the production of an existing product. The cost of quality is a tangible and noticeable testament to the upfront investments that an organisation has committed to a product. The cost of achieving and sustaining an acceptable level of product quality must, therefore, be recognised as the cornerstone of manufacturing operations. Of the many factors of importance in the pursuit of better product quality, cognitive loading is the one that is most often ignored or not recognised. In this paper, we present a methodology of assessing the impact of cognitive loading on the manufacturing cost of quality.

Keywords: Quality, Cost, Cognitive Loading, Learning Curve, Resource Loading, Manufacturing

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Biographical notes: Sharon Claxton Bommer is an Adjunct Professor of industrial engineering in the Department of Biomedical, Industrial and Human Factors Engineering at Wright State University. She has a PhD in Industrial and Human Systems with concentration in human performance and cognition. Her areas of expertise include lean manufacturing, program management and human systems integration. She has extensive practical experience in industry with more than 15 years of automotive manufacturing engineering and operation experience.

Adedeji B. Badiru is Professor of systems engineering and Dean of the Graduate School of Engineering and Management at the Air Force Institute of Technology, Dayton, Ohio. He is a registered Professional Engineer (PE) and certified Project Management Professional (PMP). His areas of expertise include mathematical modelling, quality engineering, project management,

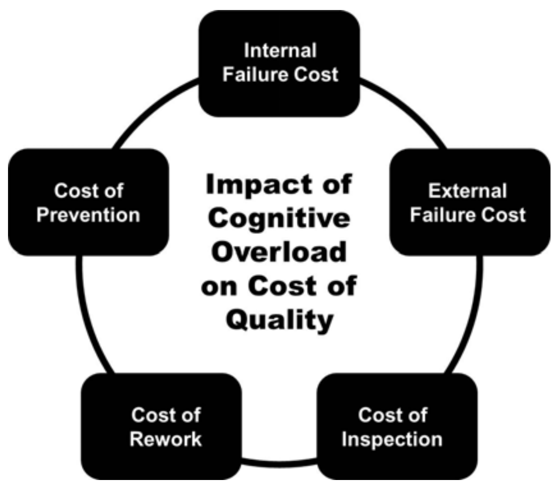
economic analysis, and learning curve productivity analysis. He is the author of several books and technical journal articles. He is a member of several professional associations.

1 Introduction

Late detected defects or failures in the manufacturing industry can lead to product recalls, re-manufacturing costs, logistic costs, shrinking of market share with potential catastrophic consequences ranging from injury or death to product shortages (Bettayeb et al., 2014). The traditional role of quality inspectors is shifting from dedicated quality inspectors to operators who perform multiple duties while attempting to perform quality inspection tasks (Pesante et al., 2001). This modifies the task from a sequential task to one that performs multitasking functions.

Multitasking is becoming more widespread in manufacturing operations. Physically demanding work that is accomplished simultaneously with a cognitive task can influence mental workload by decreasing performance (DiDomenico and Nussbaum, 2011). The objective of this research study is to identify the effects of cognitive load on performance in quality inspection. This is important because mental workload can have a direct impact on operators by affecting their performance, causing slower task performance and errors. According to Xie and Salvendy (2000), optimising the allocation of operator mental workload could decrease human errors, improve system safety, increase productivity and increase operator satisfaction. Figure 1 illustrates the potential impact of cognitive load on the costs of product quality in manufacturing.

Figure 1 Cognitive overload and various costs of quality



Quality is defined in many ways, including the following:

1 the characteristics of a product or service that convey the product's ability to satisfy stated or implied needs
2 the ability of a product to comply with requirements
3 a product's conformance to agreed standards
4 a product's state of being free of deficiencies
5 the subjective perception of a customer that a product is good
6 a value-based assessment of a product with respect to its cost.

2 Literature background

Cognitive ergonomics focuses on the interaction between tools and the operator, giving emphasis to their cognitive processes of understanding, reasoning, and the use of knowledge (Green and Hoc, 1991). It is the ergonomics of mental processes to enhance operator performance by understanding how work affects the mind and how the mind affects work (Hollnagel, 1997). A topic in cognitive ergonomics is mental workload as it affects the total person. In this respect, Geisler (2012) highlights the important elements for working happy and doing happy work, including workload, work quality expectations, work rules and regulations, workflow, workspace constraints and work duties and responsibilities.

With repetitive task operations, like manufacturing processes, there is interaction between the operator and an assigned task; this is referred to as mental workload (MWL) or simply 'workload'. This is a valuable measurement because it offers awareness as to where poor performance may result from an increase in task demands. The demands on a task or grouping of tasks may involve completing physical actions and/or executing cognitive tasks (DiDomenico and Nussbaum, 2008). The multiple resource theory (MRT) is a predictive model that assists in understanding an operator's performance ability while multi-tasking in a complex environment (Wickens, 2002).

A complex environment signifies a task that has multiple simultaneous activities which are time-shared (Liu and Wickens, 1988). When an individual performs a task, each operation deploys mental processing resources crucial to completing the task (Mitchell, 2003). Consistent with MRT, the human mind has the ability to assign resources to task demands either individually or collectively to include: visual, auditory, cognitive, motor, and speech. When task demands overlap, fewer resources are accessible to the human and MRT predicts that performance will degrade. When multiple tasks require competing resources, this could cause a compromise in system safety and effectiveness, which can impede the quality performance of the system. To assess competing resource conditions and get mental workload predictions, the human performance modelling (HPM) can be employed.

Milatovic and Badiru (2004) used a project management environment to illustrate the impact of resource loading on project quality, using activity loading as the basis for project quality assessment. Project resources (include production line operators), generally limited in quantity, are the most important constraints in scheduling of activities. In cases when resources have pre-specified assignments and responsibilities towards one or more activities, their allocation is concurrently performed with the scheduling of applicable activities. In other cases, an activity may only require a certain number of (generic) resource units of particular type(s), which are assigned after the scheduling of the particular activity. These two approaches represent the dominant paradigms in project scheduling as an indicator of project quality. To improve quality, there is always a need for a new strategy that will shift these paradigms to facilitate a more refined guidance for allocation and assignment of project resources for quality improvement purposes. In other words, there is a need for tools which will provide for more effective resource tracking, control, interaction, and, most importantly, resource-activity quality mapping. The main assumption in the methodology of Milatovic and Badiru (2004) is that project environments often involve multi-capable resource units with different characteristics. This is especially the case in knowledge intensive settings and industries, which are predominantly staffed with highly trained personnel. The specific characteristics involved are resource preferences, time-effective capabilities, costs, and resource availability. Each resource unit's characteristics may further vary across project or product production activities, but also within a single activity relative to the interaction among resource units. Finally, resource preferences, cost and time-effective capabilities may also independently vary with time due to additional factors, such as learning, forgetting, weather, type of work, quality standards, and so on. Although we do not exclude a possibility that an activity duration is independent of resources assigned to it, it is assumed that it is those resource units assigned to a particular activity that determine how long it will take for the activity to be completed; or, conversely, how high a level of quality can be achieved by the resource units. The scheduling strategy as presented above promotes a more balanced and integrated activity-resource mapping approach. Mapping the most qualified resources (or line operators) to each project activity, and thus preserving the values of resource, is achieved by proper consideration or resource time-effective capabilities and costs. By considering resource preferences and availability, which may be entered in either crisp or fuzzy form, a mental overload model enables consideration of personnel's voice and its influence on a project schedule and quality. Furthermore, resource interactive dependencies may also be evaluated for each of the characteristics and their effects incorporated into resource-activity mapping. Finally, by allowing flexible and dynamic modifications of scheduling objectives, a mental overload model can allow managers or analysts to incorporate some of the implicit knowledge and discretionary inputs into project schedules, for the purpose of increasing the quality of output.

Bommer (2016) describes the improved performance research integration tool (IMPRINT) as a human performance modelling approach, which is a computer-based discrete event simulation tool that can predict MWL. This tool was developed by the Human Research and Engineering Directorate (HRED) of the US Army Research Laboratory (ARL). IMPRINT's primary domain has been in the military sector (Mitchell et al., 2003; Krausman et al., 2005; Hunn and Heuckeroth, 2006; Chen and Terrence, 2009); however, this study broadens the use of the tool in the civilian manufacturing sector. The IMPRINT rating scale is based upon the mental resources that the operator requires to perform the work. The resources outlined in the IMPRINT rating scale are based upon MRT. IMPRINT applies a scale that contains anchors which describe the behaviours expected by each interval. Auditory, cognitive and fine motor resources are rated on a 7-point scale, speech is a 4-point scale, visual and gross motor demands are on a 6-point scale. This study utilises the resources ratings in IMPRINT to map resource demand values for each experimental treatment, and evaluate treatment differences. On the other hand, the response variable of this experiment is a measure of performance; the human error probability is evaluated.

Bubb (2005) defined human error probability (HEP) as the probability that a task under observation was achieved defective during a certain timeframe. This study uses the HEP calculation as a measure of performance error to assess the influence of cognitive load on the cost of quality. HEP divides the number of observed errors or defects by the quantity of possibilities for an error. Mathematically, HEP is expressed as follows:

$$\text{HEP} = \frac{\text{number of observed errors}}{\text{number of the possibilities for an error}}$$

3 Experimental procedure

This study simulated a manual repetitive manufacturing process with quality inspection tasks in a laboratory setting. A within subject design was utilised in a repetitive task simulation using toy building blocks. Before the experiment began, each subject was presented an informed consent and training briefing to include review of the test treatments (i.e., variant scenarios) and procedures. For each simulated treatment, the participants were provided up to five minutes to exam the work instructions and train with the toy building blocks and inspection tools. The toy blocks were selected to build with because of its likeness to an assembly process. During the simulation, the subjects had to follow a combination of colour criterion and use inspection tools (scale and calliper) to take quality measurements. There were variant instructions for each treatment. Each treatment (Table 1) was modified by type and quantity of inspection tasks to simulate the different levels of task complexity. Colour coding and measuring with tools were utilised to simulate the inspection tasks. The treatments were randomised by means of a Latin-square method to minimise any nuisance factors.

Table 1 Experiment treatments

Treatment	*Identification*	*Task elements*
Assembly with tools and inspection	ATI	Assembly with inspection tools and inspection criteria
Assembly with tools	AT	Assembly with inspection tools
Assembly with inspection	AI	Assembly task with inspection criteria
Assembly	A	Assembly task only

4 Data collection

Data was collected for each treatment using HEP as the response variable. There were 26 subjects observed in this experiment: 14 females and 12 males. Table 2 summarises the data collection for each treatment.

Table 2 Summary of descriptive statistics adapted from Bommer (2016)

Measure	*Treatment*	*M*	*SD*	*Min*	*Max*	*Range*	*95% CI*	*Effect size*
HEP (%)	ATI	0.15	0.09	0.02	0.33	0.31	[0.12, 0.19]	0.11
	AT	0.16	0.11	0	0.525	0.525	[0.11, 0.20]	
	AI	0.16	0.12	0	0.48	0.48	[0.11, 0.21]	
	A	0.09	0.12	0	0.5	0.5	[0.04, 0.14	

5 Results

An ANOVA was performed to compare the means of the operators' performance measures for the four treatments. JMP statistical software package was utilised to analyse the response variables. The test hypothesis is as follows:

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = 0 \quad \text{where } \mu_i = i^{\text{th}} \text{ treatment mean}$$

$$H_1 : \mu_1 \neq 0 \quad \text{for at least one } i$$

where $i \in \{A, AI, AT, ATI\}$ indicates the appropriate experimental condition and μ_i is the corresponding mean for HEP. The results indicated a significant effect on performance (p = 0.0492). Therefore, it is concluded that there is a significant difference among the treatments in the experiment. A post hoc test was completed to compare all the different pair combinations of treatments *i* and *j*. The hypothesis for this test is:

$$H_0 : \mu_1 = \mu_j$$

$$H_1 : \mu_i \neq \mu_j$$

where $i \neq j$ and $i \in \{A, AI, AT, ATI\}$ and $j \in \{A, AI, AT, ATI\}$ and $i < j$.

Table 3 is a summary of the post hoc comparison using the student's t test. This test indicated the performance measure of HEP was significantly different for three of the six treatment combinations.

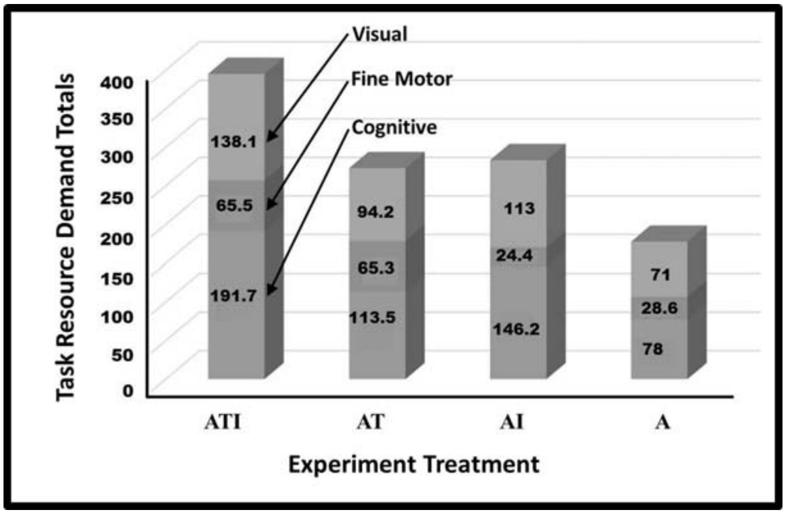
Table 3 Student's t test results

Treatment combination		*p-value*
Level	*Level*	*HEP*
AI	A	0.015*
AT	A	0.0254*
ATI	A	0.0298*
AI	ATI	0.7871
AT	ATI	0.8378
AI	AT	0.9478

Note: *p < 0.05.

Next, an analysis was performed to compare the effect of task complexity on mental workload in the four treatments. Resource mapping using the MRT scale IMPRINT was applied; Figure 2 provides a summation of the results. The results of this analysis demonstrate the influence of inspection tasks on the operator during a manual process. Treatments with the inspection task elements utilised more cognitive resources in comparison to the assembly only treatment (A).

Figure 2 Mental resource utilisation for each treatment level



6 Conclusions

The resource mapping utilising the IMPRINT rating scale provides an analysis of each treatment, and the results show the tasks with the inspection elements produced higher cognitive load for the operators. The results of this work demonstrate the influence of inspection tasks on the operator while performing a manual process. Although the simulated task would be considered rather simple, when the inspection elements were inserted into the work system, the cognitive load of the operator increased, and operator performance declined as indicated by the increase in HEP. This approach is applicable to industry, because it provides a model to analyse work design for the implication of cognitive load on the operator during quality inspections, in addition to providing a probability of error for the process design.

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