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Development of a Competency Assessment Model for Measurement of the Human Inspection Skill

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Abstract
Extensive research has already been done on visual inspection as well as on the effect of different factors on human inspection performance. However, a method should be developed to measure their inspection skill based on influencing factors. This study contributes to the literature by proposing a competency assessment model based on the influencing factors that can classify human labour into its respective skill levels. From the literature review, the influencing factors of visual inspection are listed and divided into five observed variables. A team of experts selected the significant factors with respect to the textile and clothing industry. The analytical hierarchy process is used to measure their respective weights so as to calculate the inspection performance in terms of a competency score. A numerical example is presented and the model proposed successfully determined the competency score, and inspectors are classified into their respective skill levels according to the well-defined cut-off values. This study enables organisations to classify available human labour into its skill levels and utilise them according to their capacity.

Key words: *quality control, visual inspection, decision making, inspection skill, competency assessment.*

Introduction

Since the industrial revolution, technological and economic developments have changed the environment for manufacturing and service industries. Although the current trend toward automation is altering the nature of human involvement, humans still play a major role in determining product quality and system reliability [1]. Automatic systems can perform simple and tedious tasks for an extended period of time for which human labour is poorly suited [2]. Whilst automatic systems are task specific and inflexible, with a low decision making ability; human labour is flexible with a strong decision making ability [3]. Thus, human labour remains important in most manufacturing industries, even though automation is increasing. This is why modern manufacturing systems try to augment human labour along with other essential components.

For various reasons, some industries still rely on human labour for most of their manufacturing activities, for example, manufacturing plants and firms that make leather goods, textile and garment factories, and industries ptoducing sports items [4]. In a production environment, the ability of human labour to perform a particular job increases with time, which is defined in terms of skill. The skill of human labour plays a vital role in achieving high efficiency in different processes. In an organisation, there are a number of processes where human labour is directly or indirectly involved. The focus of this study is to highlight the importance of human skill during the performance of a particular job and how performance varies from person to person. In the present era, a quality management system is more valuable than before because experts believe that the last century worked more on productivity while the present focuses on quality [5, 6]. An important part of quality management is quality control, in which different control points and checking methods are used to ensure outgoing quality. Inspection is seen as a screening or decision making process that decides the conformance or non-conformance of the product being manufactured [7, 8]. Here, the field under study is also inspection systems, which are performed by human labour.

The process of inspection mainly depends on the searching and decision making abilities of the inspector. Indeed, this role may become relatively more important as products become more complex and customer oriented [9]. Whether the product is basic or complex, human ability to do any repeative job like inspection improves with time, and the available labour can be segmented into different skill levels. Thus, in order to utilise a workforce efficiently, maintain a good competitive environment among inspectors, and keep expenditures in control, the inspection performance of individual inspectors must be measured quantitatively based on influencing factors. In the past, researchers studied the effect of different factors on visual inspection. However, there is a lack of studies on developing a method to measure the inspection skill numerically based on influencing factors so that inspectors can be classified into their respective skill levels. Similary, plenty of work has been done in the field of textile to shift conventional visual inspection towards automatic inspection [10, 11]. These studies obtained required results as far as fabric inspection is concerned [12]. While the conventional method of visual inspection by human labour is still applicable in the garment manufacturing industry. Thus, the primary goal of this study is to propose a competency-based assessment model using factors that influence visual inspection to measure the inspection skill for labour working in garment industry. The objectives of studying human-based inspection systems are to answer the following questions.

- What are the factors of visual inspection that affect the performance of an inspector?
- How can a competency assessment model be developed using the influencing factors?
- How can human labour at an inspection station be classified into different skill levels?

Literature review

Human-based inspection systems have been studied extensively with respect to different factors that can affect the performance of individual inspectors as well as the overall inspection station. Pioneering work was done by Harris [13] on the nature of industrial inspection. He presented a framework to understand and improve industrial inspection performance. Subsequently, much work was done on visual inspection based on the results of Harris [13]. A number of factors have been considered, and their effect on visual inspection performance has been evaluated. The objectives were achieved by focusing on skills such as visual search, decision making ability, and inspection strategy through online and offline training [14]. In a visual search, inspectors carefully search for flaws, while decision-making helps to decide on the rejection of the item selected. On the other hand, inspection performance is assessed on the basis of two measurements, inspection speed and inspection accuracy [15]. Accuracy is measured in terms of the hit rate, percentage of correct detection, and false-alarm rate, while speed can be measured as the search time, stopping time, and inspection time [2].

Visual search is very much affected by the speed and rigidity of pacing. In terms of accuracy, the effects of per-lot and per-item pacing were evaluated based on inspection performance. Pacing speed proved to be a significant factor for the accuracy of both per-item and per-lot; however, per-item is considered more favorable to industry [16]. The accuracy of visual inspection is particularly important for the inspection of sensitive products, such as nuclear weapons. Recently, see [17], visual inspection reliability was measured for precision manufactured parts of nuclear weapons. Multiple inspections, the inspector confidence rating, workload, and the stress of visual inspection were considered to measure the reliability in terms of accuracy and time. It was also concluded that inspection is a workload intensive task dominated by mental demand and effort [17].

The performance of human inspectors is also influenced by organisational, physical, and individual factors [14, 18]. Organisational factors include the training conducted, work methods, work procedures, policies, and social aspects. Physical factors are the tools, aids, equipment, and layout of a workplace that support the process of inspection. The individual factors are the interest, attitudes, knowledge, and skills. Improvement in performance depends on the learning behaviour, which vairies systematically for people or groups of people of different ages, genders, levels of education, and/or cultural background [19]. Researchers considered the effects of gender and age on visual inspection to determine the difference in inspection performance. However, their studies did not find significant differences in accuracy for either gender or age [19-21]. The experience of a quality inspector is also an important individual factor that contributes positively to improving inspection performance. Chan and Chiu [22] worked on experienced and inexperienced inspectors to investigate visual lobe shape characteristics and investigate their effect on inspection performance. Visual lobe roundness was evident in those inspectors who had long experience as compared to inexperienced students. Visual performance depends very much on visual capabilities, hence it is always considered a suitable parameter for the selection of labour for an inspection process. Some studies have been conducted to evaluate the effect of visual strength, the visual lobe shape, and fatigue. Visual fatigue and inspection accuracy were studied to improve inspection performance using two types of wafer coatings (Nano and gold) and two monitor sizes (14 and 19 inches). A reduction in visual fatigue and improvement in accuracy was observed with a 19 inch monitor size and gold coating conditions [22, 23].

Other than the aforementioned factors, the nature of the job and the complexity of a task also affect the performance of a human inspector. A pioneering study of task complexity in visual inspection was done by Gallwey and Drury [24]. Three types of inspection complexity were tested based on different fault types. It was concluded that inspection performance is reduced due to the complexity, which significantly affects search error, misjudgment of fault size, and decision error. Multitasking is another scenario that increases task complexity and affects inspection performance. A hybrid system was evaluated with inspectors performing a single task, three multiple tasks, and five multiple tasks. It was concluded that multiple defect types along with multitasking had a negative effect on performance [25]. Similar results were also achieved by Master, Jiang [26], who worked on human trust over time in hybrid systems. Their results showed that human trust is sensitive to the type of error made by a system.

In order to reduce task complexity, factors such as the defect distribution, defect probability, defect complexity, and number of defect types, were studied to evaluate the performance of visual search and decision-making. Results showed a negative influence of defect complexity and a positive influence of defect probability on the response factors [26, 27]. Tetteh, Jiang [28] investigated the effect of search strategy, task complexity, and pacing on inspection performance. A systematic search strategy results in superior performance and decreases the inspection time. Moreover, task complexity was also observed as a significant factor, because the easier the task, the faster and more accurate were the inspectors. Similar results were obtained by Watanapa & Kaewkuekool [29], who worked on the effect of defect complexity on inspection performance. They suggested that inspectors must be trained based upon various product complexities to increase performance and save training costs.

When improvement in the quality of human inspection is required, training is considered to be the primary intervention strategy [30, 31]. For the first time, Czaja and Drury [21] highlighted that training is a neglected area when discussing improvement in inspection performance. Their results were based on detailed experimental reports rather than only general training principles. The task performance of three different age groups was observed, and it was concluded that inspection errors were reduced due to active training, while decrements in performance due to age were also observed, albeit smaller in magnitude. After that, different types of training methods were formulated for visual inspection, and their effect on inspection performance was measured [15, 28, 32]. They concluded that a proper training program based on sound principles of training design and a well-defined methodology can bring significant improvements in inspection performance. Various training methods are used for industrial inspection, including instructional training, online training, computer-based training with feedback training, and feedforward training [15, 27, 28, 32-34]. Compared to offline training, online training was more valuable because it considered real world situations [34]. Similarly, feedforward provides prior information regarding concepts, goals, and rules to inspectors in the form of physical/verbal guidance and demonstration before the inspection

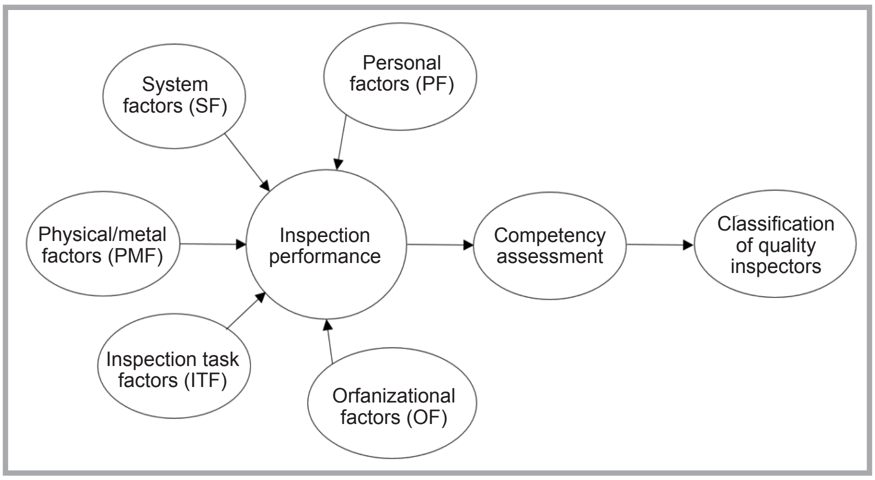

Figure 1. *Conceptual framework of proposed model.*

process [15, 35]. Feedback training, on the other hand, provides inspectors with information about their previous performance in the process in terms of the search time, search error, and decision error [15, 30].

Another effective method to improve inspection performance along with training is the use of job aids for visual inspection. A job aid means to assist the inspector during the inspection process with some type of support, such as a list, check sheet, picture, or manual. Studies have been conducted that included job aids in training for visual inspection [28, 32, 36]. A job aiding tool accompanied by training in inspection systems was evaluated by Tetteh & Jiang [28]. Their results showed that a job-aiding tool improves inspection performance with a higher detection rate in less time. In a recent study, it was concluded that prior experience can be helpful in following and designing efficient and easy-to-use job aids [36]. This comprehensive literature review has highlighted a number of factors that affect the inspection performance of inspectors. They are briefly summarised and explained in the rest of this paper and will be used to develop a competency assessment model for a human-based inspection system.

Table 1 summarises the studies published on visual inspection that were reviewed above. The focus of previous studies is classified into inspection performance measures and prominent factors concerning visual inspection. The performance measures that are used to judge inspection performance are visual search, decision-making, accuracy, and inspection time. The prominent factors are task complexity, the defect rate, defect type, search strategy, workload, stress, fatigue, job aid, and training, which have received the consideration of researchers in the past. It is evident that researchers have focused on evaluating the effect of different factors on the visual inspection of human labour. However, there has been a lack of studies on developing a method to measure the inspection skill numerically so that different inspectors can be classified into their respective skill levels. This study contributes to the literature by proposing a competency assessment model using the most influential factors of visual inspection.

Table 2. *List of identified observed variables and their indicators.*

Observed variables	Indicators	References
Personal factors (PF)	Age of the quality inspector, Interest level in current job, School/higher school education, Length of relevant experience, Good health, Relevant knowledge of the inspection process, Attitude toward work, Awareness of quality standards	[18, 19, 23, 27, 28, 34, 35]
System factors (SF)	Increase in the number of items coming from a manufacturing line, Increase in the fault percentage coming from a sewing line, Increase in the number of defect types, Fault complexity coming from a sewing line	[14, 15, 20, 25, 26, 29]
Physical/ mental factors (PMF)	Personal fatigue during the inspection process, Inspection quantity per day, Inspection time per item, Inspection errors per day, Poor hand-eye coordination, Excessive work load at an inspection station, Eye fatigue/poor eye sight, Noise and disturbance at the work-place, Decision making, Well defined work method and procedure	[2, 20, 21, 25, 31, 35, 36]
Inspection task factors (ITF)	Number of inspection tasks to be performed, More complex items to be inspected, Inspection procedure (random or systematic), Inspection of multiple products	[16, 19-21, 24-26, 30, 32]
Organizational factors (OF)	Proper data recording and reporting system, Proper communication, Work aids to support the inspection process, Monitoring the performance of the quality inspector, Incentive system and benefits, Proper layout of the inspection station, Special training programs for inspectors, Proper lighting arrangement for work stations	[2, 17, 20, 26, 30-32, 35]

Research methodology

In manufacturing industries where most of the work is carried out by human labor, the skill and performance of individual workers affects the outcome of processes significantly. The reason behind this affect is the diversification in the skills of human labour, which varies from low to high. In this senerio, work must be assigned according to the level of the worker. However, such manufacuturing industries do not have classified human labour based on working capacity. Thus, a competency assessment model needs to be developed based on the influencing factors. The model will not only classify the available human labour into its respective skills but help to promote an environment of competition among the labour. In this regard, a human based inspection system was considered, and published literature helped to identify the influencing factors of visual inspection. Based on the literature review, five observed variables: personal factors, system factors, physical/mental factors, inspection task factors, and organisational factors that are considered responsible for inspector performance were identified. ***Figure 1*** shows the conceptual framework that was followed in this study. Each variable observed and its respective indicators affect the inspection performance and can be used for competency assessment in terms of a numerical value. This value will help to classify quality inspectors into their skill levels according to their inspection performance.

The selected observed variables, consisting of multidimensional indicators that affect the inspection skill of quality inspectors, are summarised in ***Table 2***. The objective of this study is to develop a Competency Assessment Model (CAM) that can classify quality inspec-

Table 1. *Comparison of proposed model with previous literature.*

Research	Visual search	Decision making	Accuracy	Time	Task complexity	Defect rate /type	Search strategy	Work load/ fatigue	Job aid/ training	Study objective
Harris [13]		✓	✓		✓	✓		✓		Framework for industrial inspection
Czaja and Drury [21]	✓	✓							✓	Summarize different training programs
Gallwey and Drury [24]		✓	✓		✓	✓				Effect of task complexity on inspection
Wang, Lin [33]	✓		✓				✓	✓	✓	Training for strategy in visual search
Gramopadhye and Wilson [34]		✓		✓				✓	✓	Effect of feedback training and noise
Kaufman, Gramopadhye [15]		✓	✓	✓					✓	Improve inspection quality by training
Pesante, Williges [25]	✓	✓			✓	✓				Effect of multi-tasking on inspection
Garrett, Melloy [16]	✓		✓	✓						Study the effect of pacing on inspection
Ma, Drury [37]	✓			✓					✓	Impact of feedback training
Chabukswar, Gramopadhye [32]	✓		✓	✓			✓		✓	Use of aiding and feedback training
Jiang, Gramopadhye [2]		✓	✓	✓	✓	✓				Evaluation of the best system for inspection
Master, Jiang [26]			✓			✓				Measurement of trust over time
Drury, Green [38]	✓		✓					✓		Effect of fatigue factors on performance
Nalanagula, Greenstein [35]	✓		✓				✓		✓	Evaluation of feedforward training
Rao, Bowling [27]	✓	✓			✓	✓				Influence of task factors on inspection
Bhuvanesh and Khasawneh [39]		✓	✓	✓		✓				Assessment of human performance
Sadasivan and Gramopadhye [30]			✓				✓		✓	Use of technology to train inspectors
Tetteh, Jiang [28]	✓	✓		✓	✓		✓		✓	Evaluation of job aiding tools
Sadasivan and Gramopadhye [31]			✓						✓	Use of technology for inspection
Mitzner, Touron [40]	✓			✓						Evaluate age related differences
Chan and Chiu [22]	✓							✓		Effect of inspection experience
Watanapa, Kaewkuekool [29]			✓	✓					✓	Influence of training and reward
Wu and Lin [20]		✓	✓		✓	✓				Evaluation of defect complexity
See [14]	✓	✓			✓	✓			✓	Review paper on visual inspection
Heidl, Thumfart [19]	✓	✓								Gender differences in visual inspection
Lin, Chen [23]			✓					✓		Reduce fatigue problems of inspection
Charles, Johnson [36]	✓								✓	Use of job aids to assist inspection
See [17]			✓	✓		✓		✓		Determination of inspection reliability
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓	Competency assessment of inspectors

tors into their skill levels. This division is based on influencing factors that cause performance variation among inspectors. For this purpose, we need to select the significant indicators from ***Table 2*** and then measure the weight of all observed variables and their indicators using the multi-criteria decision making method – AHP.

In order to find out the significanant indicators of each observed variable, a structureal survey was conducted in the textile and clothing industry. 130 respondents (with a response rate of 52.0%) took part in the study. After anlysis, three significant factors from each observed variable were selected [41]. These indicators will be used in the development of this competency assessment model as described below.

Application of analytical hierarchy process

The objective of this study is to model different influencing factors of inspection performance into one performance

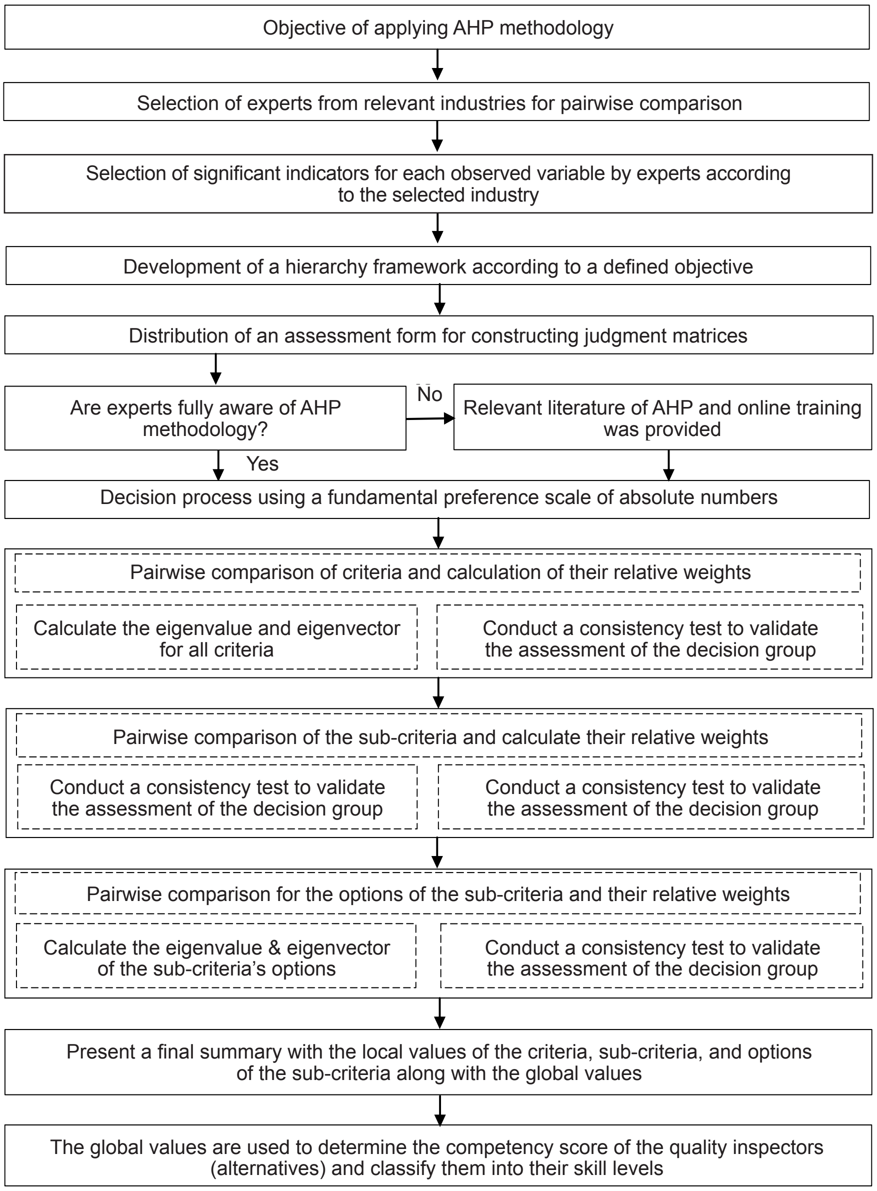

Figure 2. *Complete flow chart indicating the application of the AHP process.*

Table 3. *Selected indicators for each observed variable.*

Observed variables	Indicators
Personal factors (PF)	School/higher school education
	Length of relevant experience
	Relevant knowledge of the inspection process
System factors (SF)	Increase in the number of items coming from the manufacturing line
	Increase in the fault percentage coming from the sewing line
	Increase in the number of defect types
Physical /mental factors (PMF)	Inspection quantity
	Inspection time per item
	Inspection error
Inspection task factors (ITF)	Number of inspection tasks to be performed
	More complex items to be inspected
	Inspection procedure (random or systematic)
Organizational factors (OF)	Incentive system and benefits
	Special training programs for inspectors
	Monitoring the performance of quality inspectors

indicator. For this purpose, a mathematical model, the Analytical Hierarchy Process (AHP) developed by Saaty [42], was used. AHP is a simple decision making tool that consists of decomposing complex problems into components that are organised into sets and then finally the sets into levels to generate a hierarchal structure [43]. The method is based on a theory of measurement through pairwise comparisons relying on the judgement of experts to derive priority scales. These scales measure the intangibles and tangibles in relative terms using a scale of absolute judgement. It represents how much one element dominates another with respect to a given attribute [44]. A complete flow chart of the AHP process is shown in ***Figure 2***, and an example of each step as applied to this paper is detailed below.

Definition of the objective

The objective of this study is to develop a competency assessment model based on the factors of visual inspection so that inspectors can be classified into their respective skill levels.

Selection of experts for assessment

A manufacturing sector is nominated for the selection of experts where the process of inspection is performed by human labour. For this purpose, the value added sector of the textile industry was selected, which includes garment manufacturing (knitwear, denim, woven, etc.) and home textiles. A decision group of eight people was selected with the minimum designation of a manager who directly looks after the process of inspection. An academic researcher and an expert trainer of human labour from a service organisation accompanied this decision group. Thus, a team of experts was finalised that conducted the complete process of AHP as described in ***Figure 2***.

Selection of the significant indicators

The decision group selected three significant factors for each observed variable from ***Table 2*** based on their industrial experience and the impact of the indictors on the human inspection skill. The results are summarised in ***Table 3***.

Development of the hierarchy framework

A hierarchical framework was developed, as shown in ***Figure 3***. It includes the observed variables, their selected indicators, and the levels of each indicator. It is ob-

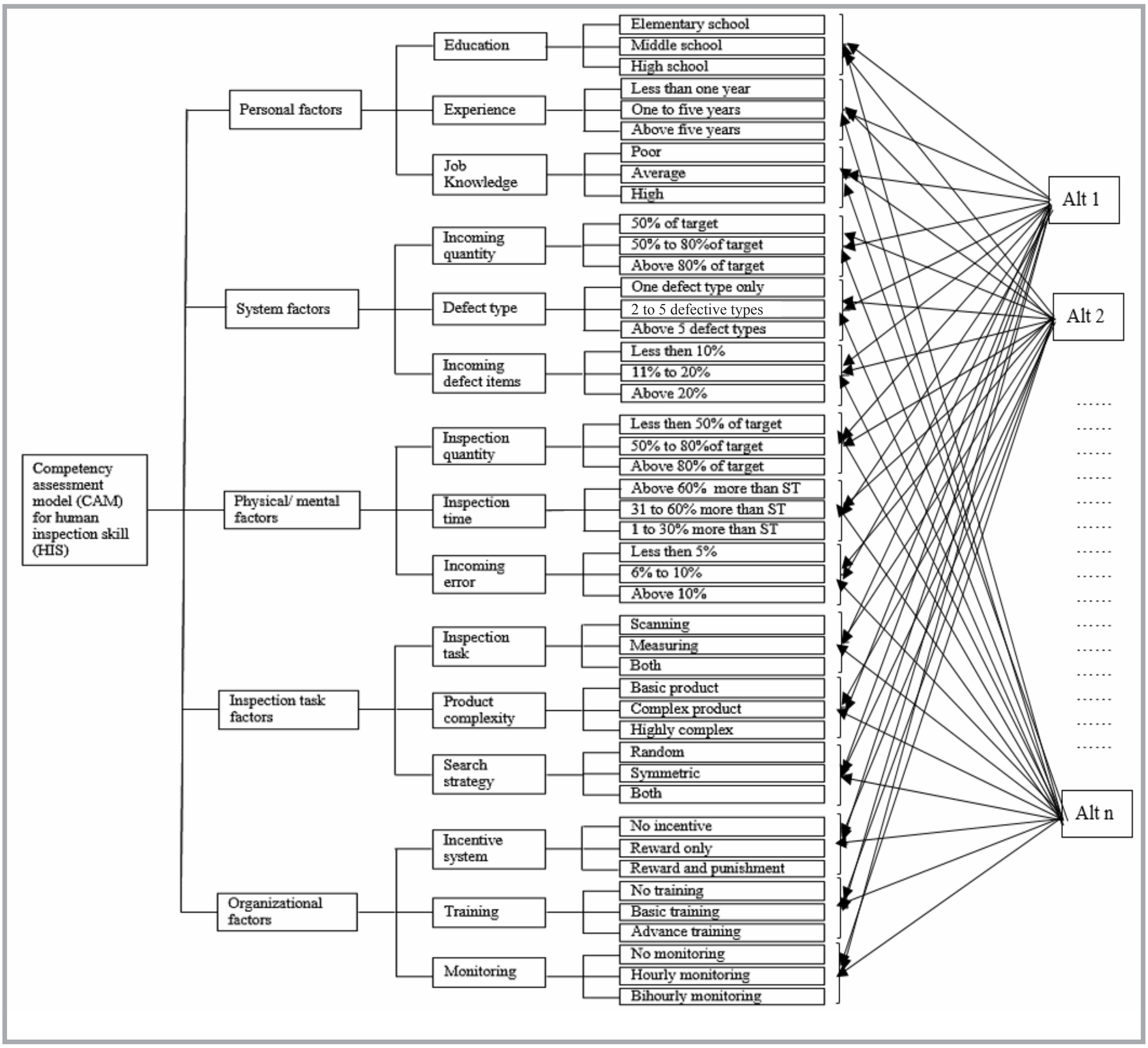

Figure 3. *Hierarchy of the competency assessment model for human inspection skill.*

vious from the hierarchy framework that the model consists of five hierarchical levels. The first level is the objective that is referred to as the competency assessment model for the human inspection skill. At the second level, the goal is divided into five main criteria or observed variables: personal factors, system factors, physical/mental factors, inspection task factors, and organisational factors. At the third level, each criterion is then divided into three sub-criteria, i.e., the selected indicators by the decision group (***Table 3***). The fourth level consists of three options of each sub-criteria that may vary with respect to each quality inspector. These options are different for each sub-criterion; for example, the education of quality inspectors may be elementary, middle or high school. Similarly, all the other sub-criteria have three options each, as shown in ***Figure 3***. However, the last level of AHP is normally called the alternatives, and in this study each quality inspector is considered as an alternative. The final weight of each sub-criterion's option will be used to assess the skill level of the quality inspectors, i.e., the alternative, in terms of the competency score, as shown in ***Figure 3***.

Decision process

In AHP, the weights are calculated by comparing each pair of criteria based on the assessment results that are finalised by the decision group. Experts are asked to make a pairwise comparison of all the elements of the criteria, sub-criteria, and options of the sub-criteria using the fundamental preference scale of the absolute numbers (***Table 4***). The final membership form of each comparison is then converted to a numerical value according to this defined scale.

Pairwise comparison of the criteria

Table 5 shows the membership functions of all the elements of the criteria that include the observed variables: PF, SF, PMF, ITF, and OF. Based on this information, a judgment matrix was developed that indicates the interrelationship of each observed variable taking into account the human inspection skill. For example, experts considered PF to be three times more important for the human inspection skill compared to SF, and two times more important compared to ITF. Similarly, PF is two times less important compared to PMF and OF.

Table 4. *Fundamental preference scale of absolute numbers.* ***Source****: [44].*

Intensity of importance	Definition	Explanation
1	Very low (VL)	Two activities contribute equally to the human inspection skill
3	Low (L)	One activity has a low contribution to the human inspection skill compared to the other activities
5	Moderate (M)	Experience and judgement strongly favour one activity over another while assessing the human inspection skill
7	High (H)	One activity is ranked high over another in terms of the human inspection skill
9	Very high (VH)	Evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	IL, IM, IH, IVH	Intermediate values
Reciprocals of above	If the first activity has the above non-zero numbers assigned to it when compared with the second activity, then the second activity has the reciprocal value when compared with the first (a reasonable assumption).	

Table 5. *Assessment of observed variables based on the human inspection skill (HIS).*

	PF	SF	PMF	ITF	OF
PF	1	L	IL^{-1}	IL	IL^{-1}
SF	L^{-1}	1	IL^{-1}	VL	IL^{-1}
PMF	IL	IL	1	L	IL
ITF	IL^{-1}	VL^{-1}	L^{-1}	1	L
OF	IL	IL	IL^{-1}	L	1

Table 6. *Random consistency index.* ***Source:*** *[45].*

N	1	2	3	4	5	6	7	8	9	10
Random consistency index (RI)	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Thus, the final judgement matrix based on the human inspection skill is as follows:

$$A_{HIS} = \begin{bmatrix} 1 & 3 & 0.50 & 2 & 0.50 \\ 0.33 & 1 & 0.50 & 1 & 0.50 \\ 2 & 2 & 1 & 3 & 2 \\ 0.5 & 1 & 0.33 & 1 & 0.33 \\ 2 & 2 & 0.5 & 3 & 1 \end{bmatrix}$$

Compute the eigenvalue and eigenvector

From the matrix above, A_{HIS}, the normalised principle eigenvector, and eigenvalue are computed. First, we need to normalise the matrix, for the purpose of which each entry in the column of the matrix A_{HIS} is divided by the sum of its respective column. The normalised matrix N_{HIS} was developed as follows:

$$A_{HIS} = \frac{\begin{bmatrix} 1 & 3 & 0.50 & 2 & 0.50 \\ 0.33 & 1 & 0.50 & 1 & 0.50 \\ 2 & 2 & 1 & 3 & 2 \\ 0.5 & 1 & 0.33 & 1 & 0.33 \\ 2 & 2 & 0.5 & 3 & 1 \end{bmatrix}}{\begin{matrix} 5.83 & 9 & 2.83 & 10 & 4.33 \end{matrix}}$$

$$N_{HIS} = \begin{bmatrix} 0.171 & 0.333 & 0.176 & 0.200 & 0.115 \\ 0.057 & 0.111 & 0.176 & 0.100 & 0.115 \\ 0.343 & 0.222 & 0.353 & 0.300 & 0.462 \\ 0.086 & 0.111 & 0.118 & 0.100 & 0.077 \\ 0.343 & 0.222 & 0.176 & 0.300 & 0.231 \end{bmatrix}$$

Then eigenvector X_{HIS} is determined by taking the average of all the values in one row of the normalised matrix N_{HIS}. This indicates the relative weight of each element present in matrix A_{HIS}. Similarly, the principle eigenvalue $\lambda_{max,\ HIS}$ is determined by the summation of the products of the eigenvector X_{HIS} and the sum of the columns of the reciprocal matrix A_{HIS}. The following results were obtained:

$$\lambda_{max,\ HIS} = 5.208,\ X_{HIS} = \begin{bmatrix} 0.1993 \\ 0.1120 \\ 0.3359 \\ 0.0983 \\ 0.2545 \end{bmatrix}$$

Consistency test

After calculating the eigenvalue $\lambda_{max,\ HIS}$, and eigenvector X_{HIS}, a consistency test was conducted to verify the assessment of the decision group. For this purpose, the value of *CI* and *CR* was calculated, the outcomes of which are presented below:

$$CI_{HIS} = \frac{\lambda_{max} - n}{n-1} = \frac{5.208-5}{5-1} = 0.0520$$

$$CR_{HIS} = \frac{CI_{HIS}}{RI_{HIS}} = \frac{0.0520}{1.12} = 0.0465$$

Where the value of *RI* for the 5×5 matrix is 1.12, as mentioned in ***Table 6***, and *n* indicates the number of elements present in the matrix. Since the value of CR_{HIS} is less than the threshold value of 0.10, the judgement made by the decision group is consistent, and the elements are properly compared. Similarly, the eigenvalue and eigenvector are computed for the sub-criteria and the options of the sub-criteria to determine their respective weights taking into acount their effect on the human inspection skill.

Compute the global values of the sub-criteria's options

Finally, based on a pairwise comparison, the weights i.e., the local values (LV) of the criteria, sub-criteria, and options of the sub-criteria are summarised in ***Table*** *7*. These values are used to determine the global values (GV) for each option of the sub-criteria using the following ***Equation (1)***:

$$GV_{sub-critreia\ options} = LV_{critreia} \times \times LV_{sub-critreia} \times LV_{sub-critreia\ options} \quad (1)$$

The resultant global values are also summarised in ***Table*** *7* and will be used to assess the skill level of the quality inspectors working in organisations or at inspection stations. In AHP, the last level consists of an alternative, which is the quality inspectors for this study. The competency score for each alternative (CS_{Alt}) is determined using the following ***Equation (2)***:

$$CS_{Alt} = \sum GV_{Alt} \quad (2)$$

The ultimate objective of this study is to divide the quality inspectors into their skill levels based on their performance i.e., their competency score. Before this, we need to define the cut-off values for the different skill levels that must be defined. For this purpose, a normalisation process was conducted to define the range of the competency scores. First, the maximum and minimum values were determined using the global values of the sub-criteria options mentioned in ***Table*** *7*. The maximum value was 0.60 and the minimum value 0.10. Then, the maximum values (0.60) were considered as the normalisation constant, and both the maximum and minimum values were divided by this normalisation constant to define the range of the competency score i.e., 0.17 to 1 of the model proposed. Based on this range, the decision group decided the cut-off values of the three different skill levels:

1. For low skill, the competency score was greater than 0.17 and less than or equal to 0.50
2. For medium skill, the competency score was greater than 0.50 and less than or equal to 0.75
3. For high skill, the competency score was greater than 0.75

Results and discussion

This section presents a numerical example to describe the application of the global values summarised in ***Table 7*** to measure the competency of the human labour performing the process of inspection. For this purpose, the values of each sub-criterion are required with respect to their respective sub-criteria options. Then, the global values were used to determine the competency score for each alternative.

Numerical example

For a numerical example, data for 1000 quality inspectors are randomly generated using Microsoft Excel. Random data comprise the value for each sub-criterion mentioned in ***Table 7*** with respect to its respective options. After that, the refinement process of random data is done by the decision group to remove any ambiguity. Finally, the data generated are used to calculate the competency score of all the quality inspectors using the global values. ***Figure 4*** shows the competency score of all quality inspectors that range from 0.27 to 0.88.

The next step is to divide the quality inspectors into their skill levels based on their competency score. Accordingly, the aforementioned cut-off values of the three different skill levels in the previous section for low, medium and high skill quality inspectors were 318, 646, and 36, respectively. However, it was observed that the cut-off values needed to be redefined, as the results of the numerical example were not realistic as far as the number of high skill inspectors were concerned. For this purpose, first a normality test was conducted using IBP-SPSS22. The test results (***Table 8***) were significant, and the competency score for all the quality inspectors based on randomly generated data was normally distributed.

The experts were involved again to redefine the cut-off values based on the normally distributed data of the competency score (***Figure 5***). Unlike the actual val-

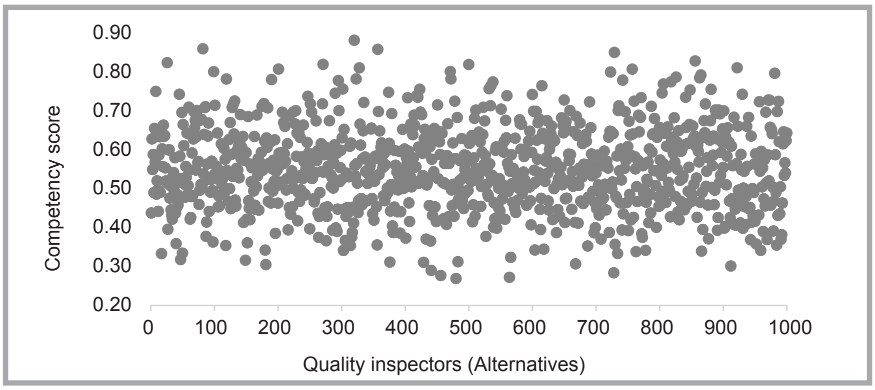

Figure 4. *Competency score of the quality inspectors based on randomly generated data.*

Table 7. *Summary of the final weights of the criteria, sub-criteria, and sub-criteria's options.*

Goal	Criteria	LV	Sub-criterion	LV	Sub-criterion's options	LV	GV
Competency assessment model (CAM) for human inspection skill (HIS)	Personal factors	0.20	Education	0.16	Uneducated	0.12	0.004
					Basic	0.32	0.010
					Above basic	0.56	0.018
			Experience	0.59	Less than one year	0.11	0.013
					1 to 5 years	0.35	0.041
					6 and above	0.54	0.064
			Job knowledge	0.25	Poor	0.11	0.005
					Average	0.26	0.013
					High	0.63	0.032
	System factors	0.11	Incoming quantity	0.16	50% of Target	0.11	0.002
					80% of Target	0.31	0.006
					100% of Target	0.58	0.011
			Defect type	0.54	One type of defect	0.06	0.004
					2 to 5 defect types	0.33	0.020
					Above 5 defect types	0.60	0.037
			Incoming defective items	0.30	Less than 10 %	0.13	0.004
					11 % to 20	0.28	0.009
					Above 30%	0.59	0.020
	Physical/ mental factors	0.34	Inspection quantity	0.17	Less than 50% of Target	0.09	0.005
					50% to 80% of Target	0.32	0.018
					Above 80% of Target	0.59	0.033
			Inspection time	0.39	Above 60% more than ST	0.08	0.010
					31 to 60% more than ST	0.26	0.034
					1 to 30% more than ST	0.66	0.085
			Inspection error	0.44	Less than 5%	0.67	0.099
					6 % to 10%	0.24	0.036
					Above 10%	0.09	0.013
	Inspection task factors	0.10	Search strategy	0.20	Scanning	0.12	0.002
					Measuring	0.32	0.006
					Both	0.56	0.011
			Inspection tasks	0.49	Basic product	0.17	0.008
					Complex product	0.39	0.019
					Highly complex product	0.44	0.021
			Product complexity	0.31	Random	0.15	0.005
					Symmetric	0.38	0.012
					Both	0.47	0.014
	Organisational factors	0.25	Incentive systems	0.42	No incentive	0.09	0.010
					Reward only	0.29	0.031
					Reward and punishment	0.62	0.065
			Training	0.46	No training	0.13	0.015
					Basic training	0.28	0.032
					Advance training	0.59	0.069
			Monitoring	0.13	No monitoring	0.08	0.003
					Hourly monitoring	0.44	0.014
					Bihourly monitoring	0.49	0.016

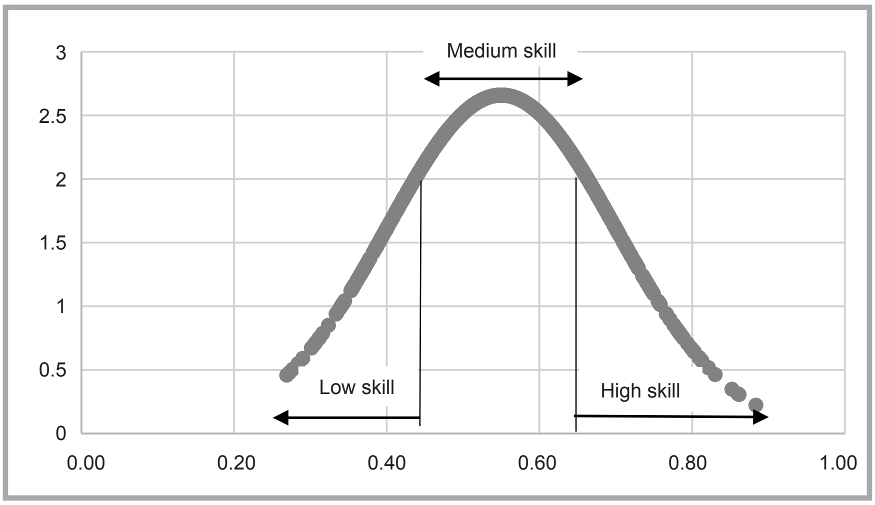

Figure 5. *Normally distributed data of the competency score.*

Table 8. *Results of the normality test.* ***Note:*** *[a] Lilliefors significance correction.*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Competency score	0.036	1000	0.004	0.997	1000	0.044

Table 9. *Number of quality inspectors based on the initial and revised cut-off values.*

	According to the initial cut-off values			According to the revised cut-off values		
	Low skill	Medium skill	High skill	Low skill	Medium skill	High skill
Cut-off values	0.17-0.50	0.50-0.75	0.75	0.20-0.45	0.45-0.65	0.62
No. of inspectors	318	646	36	165	663	172

ues of the competency score,whic ranged from 0.27 to 0.88, the experts assumed a range from 0.20 to 0.90 because it might be very rare that the final competency score would be lower than 0.20 or higher than 0.90. Thus, the revised cut-off values are described as follows:

1. for low skill, the competency score was greater than 0.20 and less than or equal to 0.45,
2. for medium skill, the competency score was greater than 0.45 and less than or equal to 0.65,
3. for high skill, the competency score was greater than 0.65.

According to the revised cut-off values, the quality inspectors were again classified into their respective skill levels. Then, the comparison was summarised for the different cut-off values, shown in ***Table 9***. This classification seems to be realistic and therefore the revised cut-off values can be used for the classification of quality inspectors or any organisation or offline station.

It can be concluded from the results of the numerical examples presented that the model proposed has successfully measured the human inspection skill by determining the competency score using randomly generated data. The resultant skill level is based on the influencing factors of the visual inspection that can affect the performance of human labour. The numerical example also helped to redefine the cut-off values of the three different skill levels based on the results. Thus, the model proposed is capable of determining the competency score and can be used to classify the human labour of an inspection station into its respective skill levels. In this way, an organisation will be able to utilise its manpower according to its performance capacity. It will also help to develop a pay scale for human labour based on its competency score. In conclusion, this method proposed will create an atmosphere of competition among human labour that will improve the individual and overall inspection performance.

Conclusions

The primary objective of this research was to study a human based inspection system with more focus on measuring the skills of labour and classify them into their respective levels. Previous studies have evaluated the effect of different factors on inspection performance. However, significant variables were not modelled to fully measure the inspection performance in terms of skill levels. This study identified the influencing factors and utilised them to design a scale. In this regard, a competency assessment model was proposed to determine the score of the inspectors based on their performance using AHP. The model proposed was applied to randomly generated data of the inspectors and their competency score was measured successfully. The results helped to define the cut off values for the three skill levels of inspectors, i.e., low, medium and high skill and all the inspectors were classified into their skill levels based on their competency score.

Firstly, the model proposed provided the most effective factors that should be monitored to get the maximum output from the inspectors. Secondly, the competency assessment enables the organisation to measure the inspection skill in the form of a competency score, providing a basis to rank the available inspectors according to their respective skill levels based on objective data. In this way, managers can efficiently utilise their manpower according to its working capacity. It also develops an atmosphere of competition among the labour in which every quality inspector will be motivated to improve his or her competency score by improving their inspection performance. Since the model proposed is based on a comprehensive framework of influencing factors, it enables mangers to focus on deficient areas that cause the low performance of an individual quality inspector. In conclusion, this research supports the idea that classifying human labour into its skill levels is more important for organisations to improve and achieve overall efficiency, because the workforce will be utilised and rewarded according to its abilities and skills. However, this aspect needs to be focused on further and practitioners should work to improve the skill levels of inspectors so that optimal results can be obtained from available manpower. It is also recommended that micro level studies be conducted in which each observed variable and its respective indicators must be investigated to evaluate their effect on inspection performance.

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