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Matolwandile M. Mtotywa (South Africa), **Sandile Mdlalose** (South Africa)

THE INFLUENCE OF ASSESSMENT ON TRAINING TO IMPROVE PRODUCTIVITY OF CONSTRUCTION COMPANIES

Abstract

The study investigated the influence of assessment on training to improve productivity of construction companies. This is important for the construction industry, which plays a critical role in a country's economic development in a continuously shifting business world, entrenching globalization, and a technology-driven economy. The investigation employed a cross-sectional descriptive quantitative design after receiving 234 responses from builders, artisans, general workers, and technicians of construction sites in Gauteng Province, South Africa. Empirical data were analyzed using STATA 14 assisted by the 'medsem' package. The results of the exploratory and confirmatory factor analysis confirmed that rework in operations (rework), optimum utilization of equipment (utilization), use of modern equipment (modernization), and identification of defects in raw material (defects) could collectively determine productivity. The AVE value was higher than 0.5 (AVE = 0.523-0.665), with all factors reliable (CR = 0.761-0.869) and the heterotrait-monotrait criterion (HTMT) ≤ 0.85 (HTMT = 0.162-0.652). Assessment has a mediation effect on theoretical and on-the-job training with productivity measures (utilization, modernization, and defects). For on-the-job training, assessment showed a complete mediation effect on modernization (effect size of 98.8% and RID = 84.6). In contrast, for theoretical training, defects showed the highest mediation (effect size = 64.3% and RID = 1.804). The implication is that well-trained employees are critical in construction sites as they can improve productivity.

Keywords productivity, training, labor improvement, mediation effect, medsem package

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Matolwandile M. Mtotywa, Ph.D., Research Supervisor, Faculty of Management Sciences, Tshwane School for Business and Society, Tshwane University of Technology, South Africa. (Corresponding author)

Sandile Mdlalose, MBA, Faculty of Management Sciences, Tshwane School for Business and Society, Tshwane University of Technology, South Africa.

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INTRODUCTION

The construction industry suffers significantly in both developed and developing countries due to delays in projects, cost overruns emanating from poor labor productivity, and the utilization of an unskilled labor force (Vaardini et al., 2016; Okoro et al., 2017; Dlamini & Cumberlege, 2021). Regardless of the challenges faced, the construction industry remains critical in infrastructure development for its contribution to the Gross Domestic Product (GDP) and economic growth in several countries around the world (Lopes et al., 2011; Berk & Biçe, 2018; Pheng & Hou, 2019; Alaloul et al., 2021). This identifies the need for the construction industry to enhance employee productivity as the failure puts further pressure on the industry, struggling with shrinkage in its market capitalization and low, sometimes as low as 2%, profit margins in large projects (Chan & Martek, 2017). This problem needs to be resolved to ensure the sustainability of this critical industry. Productivity improvements are necessary if the construction industry is to experience significant expansion. In many developing countries, poor labor performance has hindered national productivity (Manoharan et al., 2021). Obisi (2011) argued that industry leaders should ensure maximum productivity by continuously investing resources to enhance their labor force skills through training. This may be achieved through a dedicated training philosophy identifying training needs, objectives, implementation, and management. These aspects assist a construction company in applying relevant training types and methods to complement its identified needs (Singh & Mohanty, 2010). The knowledge and skills of the workforce are essential enablers of company performance, competitiveness, and advancement, and so the development of the human element can create a competitive edge (Singh & Mohanty, 2010). However, Jadallah et al. (2021) argued that the construction industry lacks systematic assessment mechanisms to measure the effectiveness of training programs, thus leaving it vulnerable to its inability to estimate the impact of such programs.

1. LITERATURE REVIEW

Over the years, considerable research has been conducted to develop construction site productivity measurements (Durdyev et al., 2016). However, these systems are not always effective as operations are not continuous and repetitive, such as in the manufacturing industry. The construction industry is not easy to measure productivity due to the variety of sub-products and sub-services rendered by this industry (Durdyev et al., 2016). They further argued that residential buildings, civil engineering projects, road construction, sewer construction, mechanical and electrical construction, and factory buildings require different types of technologies and construction methods. Thus, it is not easy to accurately measure productivity levels in the construction industry, notably as labor requirements differ from sector to sector. Nonetheless, as construction sectors show varying degrees of labor intensity, it is easy to understand why or how labor training will affect various sectors within the same industry (Fenner et al., 2018).

Kirkpatric (1959) and Yaqoot et al. (2021) argued that training effectiveness could assist companies in comprehending the many evaluation approaches employed in training. Kirkpatrick (1998) asserted that training and its efficacy must be evaluated at every level. Moreover, it should involve participants' reactions to the training program, as well as their learning, behavior, and outcomes. Such evaluation aligns with the present study attempting to understand the influence of training on productivity, with assessment having a mediation effect on this relationship. Understanding training effectiveness is critical within the construction industry because it is among the highest labor-intensive industries. Here, labor productivity is a crucial aspect of construction projects within most developing countries (Boadu et al., 2020; Bamfo-Agyei et al., 2022). These methods have been embedded for decades and use a mixture of permanent and casual labor, with casual labor being the most common (Jairam & Allopi, 2018). Amid technological changes, South Africa and other developing countries find themselves with a manual-automation job dilemma due to high levels of unemployment, so manual labor is seen as one of the central interventions to decrease unemployment (ILO, 2019; Mtotywa et al., 2022).

According to Shehata and El-Gohary (2011), there is no standard definition of productivity. Hence, any confusion regarding productivity is due to non-standard terminology. For this reason, labor productivity may be improved by reducing variation in labor productivity, particularly because daily labor productivity may vary, so it can also improve on a daily basis. Oeij et al. (2012) advised that productivity is the inputs-to-output ratio. However, this may be an oversimplification that violates reality as other variables may affect the output, and a combination of variables may result in a completely different result. Likewise, the human factor is also influenced by other variables, depending on the nature of the job (Danso, 2014). External factors affecting the construction process, which subsequently influence productivity, are those linked directly to employee productivity. They include reworks, inappropriate equipment utilization, poor raw material quality, a lack of labor experience, and use of modern equipment (Hwang et al., 2009; Obisi, 2011; Dwyer, 2013; Safa et al., 2014).

The productivity of a major industry such as construction is significant, as it contributes to the economic growth of any nation. According to the industry's economic size, an increase in labor productivity achieved through workforce training

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should significantly enhance industry productivity (Kazaz et al., 2016). Numerous studies have been conducted to identify factors affecting productivity in construction projects, but the lack of relevant training and skills was highlighted as some of the main influencing factors (Mahamid, 2013). Training is the deliberate and methodical teaching and learning of a set of skills, norms, concepts, or attitudes meant to raise the level of performance in an individual or a group (Alsalamah & Callinan, 2021). Training is one of the most effective methods implemented by most companies to enhance employee productivity and workplace performance (Alipour et al., 2009; Dermol & Čater, 2013; Noe & Gerhart, 2015). Over and above performance, the global construction environment is dynamic, demanding a workforce that can adapt to change (Steensma & Groeneveld, 2010). However, as of 2012, an evident downward trend of skilled labor in the industry pointed to a general shortage of builders at below 50% (CIDB, 2015).

Hughes and Thorpe (2014) researched the connection between education and productivity. They concluded that productivity is the ratio of production to all or part of the resources – labor, capital, energy, and raw materials – used to produce the output. To achieve optimum productivity, one requires the effective utilization of labor, precise and full designs, no delays other than those caused by weather, safe working conditions, excellent craftsmanship, and the absence of litigation at the project's conclusion. Because training directly affects employees' levels of productivity in the workplace, the most effective strategies for workplace improvement should focus on training and productivity (Aghazadeh, 2007; Manoharan et al., 2021). Thus, the most important connection that needs to be made is between a process and a problem and, more specifically, how the act of training (the process) is directly related to an increase in productivity (the problem). This indicates that training is not only required but is also essential to every facet of the company. Barrett (2012), supported by Leidner and Smith (2013), highlighted that training investment can assist companies in concurrently improving productivity and retaining employees. The overall benefits to the company should include improved quality performance, efficiencies, and more valuable customer service, thus making the company more profitable (Naoum, 2016). Eisele et al. (2013) investigated the issue of low productivity in various sectors and discovered that most companies respond by intensifying their focus on learning, training, and development. Gauld and Miller (2004) argued that training content should include both theoretical and practical on-the-job aspects to help employees effectively develop the necessary skills.

The developed theoretical framework has assessment as the mediator (M). Darmawan and Jaedun (2020) explained that assessment is critical to monitoring learning progress, determining the knowledge, and estimating development strengths and gaps. Such assessment is a learning process characterized by reflection on capacity and capability and may be utilized as an adjustable base – critical within different learning approaches (Steensma & Groeneveld, 2010). Hammad et al. (2011) confirmed that training supervisors and members on the ground is crucial to productivity improvement in construction sites, particularly as construction companies rarely hesitate to train employees in specific skills, such as how to operate a new piece of equipment. The benefit of training is almost immediately measurable, and the employee is usually more productive immediately after mastering the new skill. This implies that for the purpose of the present study, the effectiveness of training should be measured through a process rather than measuring the outcome of the process. This method was applied due to its complexity and other contributing factors that might affect productivity outcomes.

Inankul (2016) highlighted that learning is essential to gain knowledge and skills. This can be done in a classroom environment (theoretical training) or on-the-job training. Well-trained employees tend to produce error-free work. Errors in a construction site environment are the main cause of project overruns and escalating project costs resulting from an attempt to rework construction. Okoro et al. (2017) posited that education and training increase labor knowledge from practical on-the-job training sessions, increasing productivity. They further argued that training and education of the workforce should be continuous and satisfactory for any company to realize their investment. Figure 1 shows the theoretical framework for the present study.

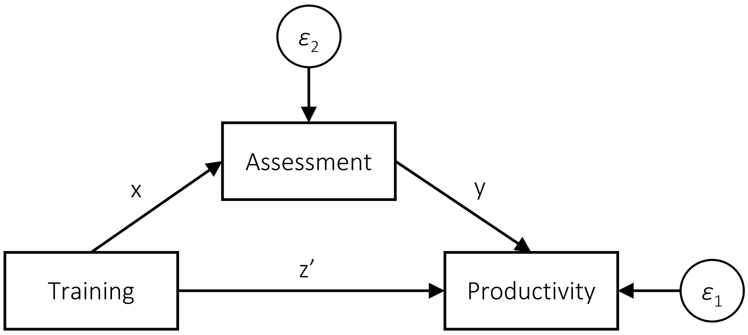

Figure 1. Theoretical model

Therefore, this study aims to investigate the mediation effect of assessment on the relationship between training and productivity in construction companies. This is important in a business world that is continuously shifting and entrenching globalization and a highly technology-driven economy. Such turbulence and pressures force companies to reduce operational costs and improve productivity to compete more effectively against local and international rivals. By understanding the effect of training on productivity, the construction industry can more efficiently develop relevant processes aligned to improving its productivity. Thus, the present study formulated the following hypotheses:

H1: *Training has a statistically significant effect on productivity in construction companies.*

H2: *Assessment has a mediation effect on the relationship between training and productivity in construction companies.*

2. METHODS

The study obtained ethical clearance from the Tshwane University of Technology, with ethical clearance number [FCRE2017/FR/09/005-MS (2)]. This study's cross-sectional descriptive quantitative research design sets out to determine the relationship and mediation effect on the training of employees and their productivity in construction companies. The population was the labor force within construction sites in Gauteng Province, South Africa. Study participants included general workers, artisans, builders, and technicians. However, the total population force was unknown as there was no readily available database within an industry with a high proportion of casual labor. Therefore, the sample was calculated as per the recommendations of Naing et al. (2006):

$$n = \frac{Z^2 P(1-P)}{d^2}, \tag{1}$$

where n represent sample size, while P = expected proportion, Z statistic (Z) = 1.96, and d = precision. The sample size was 384, and the study used a non-probability sampling method employing a convenience sampling technique. From this sample, 234 responses were obtained, equating to 60.9%, which is in line with a 60% response rate of a manual survey (Nulty, 2008). The instrument of the study was developed from Alipour et al. (2009), Hammad et al. (2011), Obisi (2011), Hughes and Thorpe (2014), and Mittal et al. (2016) and adapted accordingly for the study. The targeted respondents were in construction sites, and not all had access to electronic devices to complete the survey questionnaire. As such, the preferred method for data collection was manual in different construction sites, where each respondent obtained a printed copy of a questionnaire to complete and return. Collected data were analyzed with Stata 14 to obtain descriptive statistics, exploratory, confirmatory factor analysis, and the correlation matrix. The mediation effect was analyzed using the 'medsem' package in Stata 14 (Mehmetoglu, 2018). The mediation analysis model of the study, based on the approach by Mehmetoglu (2018), is:

$$P = \alpha_o + cT + \varepsilon \tag{2}$$

where P = productivity, T = training, α = coefficient, and ε = error term. The mediation path is estimated by regressing on-the-job and theoretical training with productivity factors: minimizing rework, effective utilization of the equipment, use

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of modern equipment (modernization), and identifying raw material defects.

As such the path x should be estimated by regressing the mediator on independent variables as well as the mediator on dependent variables by:

$$M = \alpha_o + xT + \varepsilon, \quad (3)$$

$$P = \alpha_0 + yM + z'T + \varepsilon. \quad (4)$$

Sobel and Monte Carlo resampling-based approach was used to determine indirect effects and effect size (RIT and RID) with the following equations (Zhao et al., 2010):

$$RIT = \frac{x \cdot y}{(x \cdot y) + z}. \quad (5)$$

The effect size of the indirect effect is measured by:

$$RID = \frac{x \cdot y}{z}. \quad (6)$$

3. RESULTS

Demographic statistics showed that 76% of the respondents were male and 24% were female, with the majority aged between 26 to 35 years (56%), while those in the 36 to 40 years bracket represented 21% of the respondents. Most (42%) of the respondents had completed matriculation and had trade experience (35%), with almost two-thirds (64%) reporting five years or less of working experience. These respondents were mainly general workers (41%) and builders (23%), followed by artisans at 20% and artisan assistants at 9% (Table 1).

Table 1. Demographic profile of the respondents

Variable		Frequency (n)	Percent frequency (%)
Gender	Male	153	76%
	Female	49	24%
Age	Less than 26 years	28	14%
	26-30 years	66	33%
	31-35 years	47	23%
	36-40 years	42	21%
	41 years and above	18	9%
Educational level	Below Grade 12	34	17%
	Matric	84	42%
	Trade	71	35%
	Diploma or above	13	6%
Working experience	Less than 1 year	17	8%
	1-3 years	64	32%
	3-5 years	65	32%
	5 years or more	56	28%
Occupation	General worker	82	41%
	Artisan assistant	18	9%
	Builder	47	23%
	Artisan	41	20%
	Technician	13	6%

The descriptive statistics of training items had a mean (M) range of 3.15-3.59 (Table 2). The respondents mostly agreed with the statement "The trainer is always available for consultation" – TR01 with mean = 3.59 (SD = 1.115). This was followed by the statement "I prefer practical training than theoretical training" – TR11 (M = 3.55, SD = 1.362) and then "Practical exercises are available during training" – TR03 (M = 3.54, SD = 0.993). On the other hand, the least number of respondents agreed with the statements that they are "Given enough chance to prepare for tests and assignments" – TR15 (M = 3.15, SD = 0.976), "Assessment is generally difficult" – TR16 (M = 3.17, SD = 0.809), then "Trainer has dynamic and interesting presentation style" – TR06 (M = 3.17, SD = 1.099).

The 17-item scale for training was evaluated for construct validity using exploratory factor analysis. The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = 0.887) and Bartlett test of sphericity (χ^2 (136) = 1769.7, $p < .001$) confirmed the suitability of the factor analysis (Loehlin & Beaujean, 2017; Watkins, 2018). Three factors were extracted with a percentage variance of 85.6%, namely theoretical training, on-the-job training, and competency assessment, with loading factors greater than 0.4 (Table 3).

The productivity instrument employed included 16 items with mean values that ranged from 2.96 to 3.59 (Table 4). The highest mean was variable – VAR5 "I know every equipment required to execute my work" with M= 3.59 (SD =1.101), and the lowest mean was VAR 16 – "I never use rejected raw material" (M = 2.96, SD = 0.942).

The suitability of the exploratory factor analysis was confirmed by the KMO = 0.851 and Bartlett's

Table 2. Descriptive statistics of training items

Statements		Mean	SD
The trainer is always available for consultation	TR01	3.59	1.115
Training equipment is always available	TR02	3.51	1.012
Practical exercises are available during training	TR03	3.54	0.993
Trainers allow trainees to explore	TR04	3.51	0.932
Trainers give opportunity for exercises in class	TR05	3.35	1.350
Trainer has a dynamic and interesting presentation style	TR06	3.17	1.099
Discuss the practical application of the subject matter	TR07	3.23	1.067
Trainers set out clear objectives for each lesson	TR08	3.30	1.061
Trainers prove the formative and informative assessment	TR09	3.34	1.010
Employees get a fair chance during training	TR10	3.39	1.143
I prefer practical training to theoretical training	TR11	3.55	1.362
Assessment exercises are based on the work covered	TR12	3.33	0.996
Evaluation sheets are fair	TR13	3.32	1.081
Trainer issue relevant assignments. tutorials and test	TR14	3.30	1.089
Given enough chance to prepare for tests and assignments	TR15	3.15	0.967
Assessments are generally difficult	TR16	3.17	0.809
Training material is user friendly	TR17	3.38	1.004

test (χ^2 (20) = 1506.5; *df* = 20; p < .001 (Table 5). All the factor loadings were statistically significant, *p* < .001, implying that all these indicated variables are significantly related to their respective factors. Four factors were extracted with loading factors higher than 0.4, named rework in operation (rework), optimum utilization of equipment (utilization), use of modern equipment (modernization), and identification of defects in raw material (defects).

The convergent validity was analyzed using (AVE). It is a measure of how much variance a construct captures in comparison to how much variance is attributable to measurement error:

Table 3. Exploratory factor analysis of training items

Factors	Statements	Loading factor	A
Theoretical training	TR05, TR06, TR7, TR08, TR09	0.6277-0.789	0.868
On-the-job training	TR02, TR03, TR11, TR01, TR04, TR10	0.507-0.779	0.845
Competency assessment	TR12, TR13, TR14, TR15, TR16, TR17	0.452-0.6104	0.766

Note: KMO = 0.887. Bartlett test of sphericity: χ^2 = 1769.7; df = 136; p < .001. Variance extracted = 85.6%.

Table 4. Descriptive statistics of productivity items

Statements		Mean	SD
There are always reworks to be done in my job	VAR1	3.34	1.113
It takes long to rework material	VAR2	3.30	1.034
My working conditions force me to do reworks	VAR3	3.18	1.066
Projects are always delayed due to reworks	VAR4	3.41	1.095
I know every piece of equipment required to execute my work	VAR5	3.59	1.101
Every operation equipment is well maintained	VAR6	3.20	0.928
Tools/equipment is always available to do the job	VAR7	3.25	0.973
I am aware of the performance expectation for every piece of equipment that I am using	VAR8	3.46	0.986
I always use modern equipment	VAR9	3.08	1.121
Modern equipment performs better than the old equipment	VAR10	3.37	1.063
Detailed training is given for every new machine introduced	VAR11	3.27	1.006
I find it easy to adapt to new equipment	VAR12	3.08	1.057
Modern equipment is more reliable than the old equipment	VAR13	3.41	0.976
I have to do a rework on the raw material	VAR14	3.27	1.071
I am well trained identifying defective material	VAR15	3.34	1.009
I never use rejected raw material	VAR16	2.96	0.942

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Table 5. Exploratory factor analysis of productivity items

Factors	Statements	Loading factor	% Variance	Eigen value	α	AVE	CR
Rework	VAR1, VAR2, VAR3, VAR4	0.772-0.802	0.357	5.716	0.8375	0.624	0.869
Modernization	VAR9, VAR10, VAR12, VAR13	0.699-0.828	0.156	2.489	0.7788	0.570	0.841
Defects	**VAR11,** VAR14, VAR15, VAR16	0.599-0.757	0.087	1.388	0.7986	0.515	0.761
Utilization	**VAR5**, VAR6, VAR7, VAR8	0.501-0.809	0.066	1.051	0.7851	0.534	0.770

Note: KMO = 0.851. Bartlett test of sphericity: χ^2 = 1506.5; df = 20; p < .001. All factor loadings were statistically significant, p < .001. Variables in bold – excluded in the final factor.

$$AVE = \frac{\sum \lambda^2}{n}, \qquad (7)$$

where λ is the factor loadings while n is the indicators in the factor. The results showed AVE higher than 0.5, confirming convergent AVE = 0.523-0.665. The composite reliability (CR) was assessed by:

$$CR = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + (\sum \varepsilon)}, \qquad (8)$$

where ε = 1-λ. The CR results confirmed that all factors were reliable with CR = 0.761-0.869. Heterotrait-monotrait criterion (HTMT) determined the discriminant validity analysis based on the formula provided by Henseler et al. (2015):

$$HTMT_{ij} = \frac{W}{\sqrt{R \cdot Q}}, \qquad (9)$$

where Q = average monotrait-heteromethod correlation, W = average heterotrait-heteromethod correlations, R = average monotrait-heteromethod correlations.

The HTMT values for all variables were less than 0.85 (Kline, 2011). The range of the variables of HTMT was between 0.162-0.652. These results confirm the discriminant validity (Table 6).

The Pearson correlation matrix shows that there was a statistically significant and positive strong correlation between on-the-job training and rework (r = 0.536, p < .001) and on-the-job training defects (r = 0.571, p < .001) (Table 7). There was also a statistically significant and positive strong correlation between on-the-job training and theoretical training (r = 0.575, p < .001) as well as on-the-job training and assessment (r = 0.608, p < .001). There was a statistically significant positive but weak relationship between assessment and rework, and no statistically significant correlation existed between modernization and rework.

The direct and indirect effects of the competency assessment on training and productivity, which assessed the mediation effect, are tabulated in

Table 6. HTMT for a measure of discriminant validity

Factors	Rework	Utilization	Modernization	Defects
Rework	–	–	–	–
Utilization	0.532	–	–	–
Modernization	0.162	0.593	–	–
Defects	0.623	0.652	0.561	–

Table 7. Correlation matrix of the training and productivity factors

Factors	1	2	3	4	5	6	7
1. Rework	–	–	–	–	–	–	–
2. Utilization	0.417***	–	–	–	–	–	–
3. Modernization	0.0321	0.355***	–	–	–	–	–
4. Defects	0.484***	0.395***	0.301***	–	–	–	–
5. Assessment	0.273***	0.445***	0.559***	0.494***	–	–	–
6. Theoretical	0.417***	0.431***	0.524***	0.355***	0.581***	–	–
7. On-the-job training	0.536***	0.499***	0.297***	0.571***	0.608***	0.575***	–

Note: * p < 0.05, ** p < 0.01, *** p < 0.001.

Appendix A. The path coefficient of rework → theoretical training showed a statistically significant positive relationship, $\beta = 0.483$ (10.90), $p < .001$. However, there was no statistically significant relationship with the path rework → assessment. Sobel test indicates that z = 0.768, $p < .01$ with confidence interval [–0.060, 0.138] with zero falling between the lower and upper band; the Monte-Carlo also confirms this for the indirect effect. This indicates that the assessment did not have a mediation effect between training and rework. Similar outcomes were found for the on-the-job training, indicating that assessment did not mediate the relationship between on-the-job training and rework. The results also showed a statistically significant positive relationship between theoretical training and utilization, $\beta = 0.260$ (3.81), $p < .001$. There was also a statistically significant positive relationship in the path utilization → assessment, $\beta = 0.390$ (4.55), $p < .001$, and theoretical training → assessment, $\beta = 0.466$ (10.22), $p < .001$.

With all the paths being statistically significant, it can be concluded from the study that assessment partially mediates the relationship between theoretical training and utilization of equipment. The Sobel and Monte-Carlo tests for indirect effect confirm the mediation effect, with RIT indicating an effect size of 0.412, meaning that 41.2% of the effect (total effect) of the theoretical training on utilization is mediated by assessment. The RID shows that this mediation effect of assessment is about 0.7 times as large as the direct effect of theoretical training on utilization. These results are similar for the on-the-job training; however, the effect size is smaller, with RIT = 33.4% and RID = 0.502. This indicates that the assessment has a more substantial mediation effect on the theoretical training than on-the-job training on utilization. All paths of theoretical training, modernization, and assessment were statistically significant, indicating a partial mediation effect of assessment on the relationship between theoretical training and modernization. These results were confirmed by the Sobel test with confidence interval [0.131, 0.300] and Monte-Carlo test [0.130, 0.300] for indirect effect with zero not falling between the lower and higher confidence intervals. This mediation effect, with RIT, indicates an effect size of 0.427, so 42.7% of the effect (total effect) of the theoretical training on modernization is mediated by assessment. In the on-the-job training, there was a complete mediation with an effect size of 98.8% and RID = 84.6, showing that this mediation effect of assessment is about 84.6 times as large as the direct effect of on-the-job training on modernization. Defects path were all statistically significant in both theoretical training, defect, and assessment, as well as on-the-job training, defects, and assessment. This indicates that assessment has a partial mediation effect on the relationship between training (theoretical and on-the-job) and defects. The effect size for assessment mediating theoretical training on defects was larger, 64.3% (RIT = 0.643), compared to the assessment mediating theoretical and on-the-job training on defects, 27.3% (RIT = 0.273). This means that *H1* and *H2* are partially accepted.

4. DISCUSSION

The results of the exploratory and confirmatory factor analysis confirmed that rework in operation (rework), optimum utilization of equipment (utilization), use of modern equipment (modernization), and identification of defects in raw material (defects) could be collectively used to determine the productivity in a construction site. This is congruent to other studies that have identified these factors as significant influencers of productivity (Ayağ, 2007; de Lacalle & Mentxaka, 2008; Obisi, 2011; Mahamid, 2013; Danso, 2014).

These results confirm the importance of training in factors that improve productivity. In the four factors evaluated for productivity, assessment has a better mediation effect on the theoretical training on utilization as well as theoretical training on defects. At the same time, it had a better mediation effect in on-the-job training on modernization. Classroom training (theoretical) can prepare employees to yield significant benefits to the workforce by identifying excellent and substandard quality material delivered. On the other hand, inadequate training in this area may have a negative impact on industrial production (Mittal et al., 2016). Utilization of construction equipment and tools also has an impact on productivity. These objects are created as aids, suggesting that modern tools are designed to serve numerous roles (Dwyer, 2013). Ayağ (2007) clarified that the choice of appropriate tooling is a critical issue in the construc-

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tion industry for decades. Improper selection of machine tools may have a negative impact on the company's productivity, precision, flexibility, and responsive construction capabilities. Abd El-Razek et al. (2008) highlighted that in the construction industry, a shortage of equipment results in employees using the wrong equipment for the job. Employees are trained to identify which equipment to use and where. However, due to facility constraints and tight schedules, employees, at times, are forced to utilize what is available to keep the job going. Productivity is also influenced by using poor-quality raw materials or materials with defects.

According to Safa et al. (2014), an essential function of the construction site is to assess whether the materials used meet the specified standard in the statement of works. Work needs to be redone when materials do not meet such standards. This can adversely influence productivity regarding both time and costs as this might involve demolishing the already constructed sections and reworking the project with the appropriate and correct quality of materials. On-the-job training is recommended by Alipour et al. (2009) because it helps teach workers the specifics of their jobs. The results show that this form of learning is vital in the use of modern equipment, with the assessment showing complete mediation. This is crucial because co-workers and mentors typically provide on-the-job training to help employees get comfortable with their jobs and equip them with the necessary job-related skills. More knowledgeable individuals might deliver it in the form of coaching or instruction. This is important as it is not easy to obtain modern equipment, so it must be fully utilized if acquired. Danso (2014) highlighted that the high cost of modern equipment is one of the reasons why companies fail to afford and utilize modern equipment even though it can help to improve productivity. Its usefulness is also enhanced with the use of technology, which has improved construction efficiency, accuracy, and quality (Mottaeva et al., 2016).

Mahamid (2013) posited that rework is the leading contributing factor that negatively affects productivity in the construction industry. What is evident from the results is that the handling of rework can be improved by both theoretical and on-the-job training. This must be done because builders who do not get proper training produce poor-quality work on sites. This is usually discovered during inspection or at the handover stage. Sub-standard work results in rework, affecting the overall delivery of the project. When the project experiences delays, project managers tend to speed up the project by ceasing some activities or aggressively rescheduling activities. This practice allows less time to complete activities, which is detrimental to the project and adds to the pressure of adhering to time schedules; the result is that the quality of work and the quest to meet project deadlines may be compromised. By implication, contractors in heavy industrial projects should invest more effort in tracking and minimizing the impact of reworks on project cost, and by doing so, this will ultimately improve the cost performance of projects (Hwang et al., 2009). Obisi (2011) suggested that a well-trained employee would make greater economic use of materials and equipment, which would go a long way toward minimizing wastage and reworks. Thus, training enables employees to identify defective material before installation and prevent unnecessary reworks. It also offers leadership the confidence to delegate and have faith in the decisions employees make on sites.

South Africa is still a developing country, and per the National Development Plan vision 2030, it aims to better integrate the country's rural areas into urban areas (National Planning Commission, 2012). This is accomplished by effective land reform, infrastructure development, and employment creation within the construction industry to reduce inequality and poverty. Randeree and Chaudhry (2012) concluded that in a culturally diversified environment, job satisfaction has a tremendous effect on the productivity of employees. Training is the main factor influencing productivity (Naoum, 2016). Teizer et al. (2013) emphasized the importance of investment in labor, indicating that an investment of only 1% of a project labor budget could therefore result in a double-digit productivity return. The implication of the present study suggests a direct link between productivity and training. Construction companies must use training to improve productivity for improved competitiveness and sustainability. This study determined the extent to which training affects productivity in the construction industry. Obisi (2011) argued that industry leaders ensure maximum productivity by continuously investing resources into enhancing their labor force skills and specific emphasis on training to yield positive results. This is accomplished through a training philosophy that identifies training requirements and the evaluation of specific training requirements. These aspects assist a company in applying relevant training types and methods to complement the identified needs (Singh & Mohanty, 2010). To improve its efficiency, local and international companies within the industry need to use labor to their advantage to gain a competitive edge over their rivals, thereby securing maximum contributions from their labor force throughout the supply chain.

CONCLUSION

The present study investigated the influential role of assessment on training to improve productivity in construction companies. It revealed that training significantly impacts construction companies' productivity showing a direct link between productivity and training. Both on-the-job and theoretical training, coupled with the assessment in place, are critical to improving the productivity factors, such as optimum utilization of equipment (utilization), use of modern equipment (modernization), and identification of defects in raw material (defects). With these results, it can be concluded that the construction industry needs to implement comprehensive training on its site to improve its productivity. Training is also critical for construction in a demanding and changing industry influenced by digitalization and technology growth. These findings confirm that training remains a critical factor needed to improve productivity in this industry. However, maximum output is achieved if training effectiveness is assessed and decisions are made based on the return on investment. Therefore, regardless of the industry, the company strategy is parallel to profit maximization.

It is recommended that construction industry companies continuously offer training to improve site productivity. Formalized and accredited training would be ideal, as it can allow them to access mandatory and discretionary grants from Sector Education and Training Authorities (SETAs). Furthermore, the present study recommended that this training be optimized using technology platforms such as online applications. Thus, it can be both accessible, continuously available, and with minimum effort and cost after the initial cost to respond to the challenges of the high level of casual workers in the industry, a figure which is prone to a high turnover.

Based on the focus and outcomes of the study, it is suggested to perform additional research that can quantify the improvements from a financial perspective regarding improved productivity resulting from training to fully understand the return on investment of training within the construction industry. Furthermore, as this study was focused on general construction, it will be of value to conduct the same study to understand if the training on the productivity factor is homogeneous or heterogeneous. This will ensure that training on productivity improvement factors and the mediation effect by assessment is optimized and that companies in the construction industry fully leverage benefits.

AUTHOR CONTRIBUTIONS

Conceptualization: Matolwandile M. Mtotywa, Sandile Mdlalose.
Data curation: Sandile Mdlalose.
Formal analysis: Matolwandile M. Mtotywa, Sandile Mdlalose.
Investigation: Matolwandile M. Mtotywa, Sandile Mdlalose.
Methodology: Matolwandile M. Mtotywa, Sandile Mdlalose.
Project administration: Sandile Mdlalose.
Resources: Sandile Mdlalose.

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Software: Matolwandile M. Mtotywa, Sandile Mdlalose.
Supervision: Matolwandile M. Mtotywa, Sandile Mdlalose.
Validation: Matolwandile M. Mtotywa.
Visualization: Matolwandile M. Mtotywa, Sandile Mdlalose.
Writing – original draft: Matolwandile M. Mtotywa.
Writing – review & editing: Matolwandile M. Mtotywa, Sandile Mdlalose.

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APPENDIX A

Table A1. Direct and indirect effects of the competency assessment on training and productivity

Paths		Theoretical training				On-the-job training			
		Rework	Utilization	Modernization	Defects	Rework	Utilization	Modernization	Defects
Direct effect (SEM)	T → M (Path x)	0.483(10.90)***	0.466(10.22)***	0.460(9.53)***	0.461(10.31)***	0.512(10.49)***	0.521(10.65)***	0.528(10.35)***	0.497(10.01)***
	M → P (Path y)	0.081(0.77)	0.390(4.55)***	0.468(5.87)***	0.532(6.09)***	−0.061(−0.64)	0.343(4.14)***	0.671(8.03)***	0.325(4.11)***
	T → P (Path z’)	0.405(4.89)***	0.260(3.81)***	0.289(4.46)***	0.136(1.99)*	0.632(7.60)***	0.357(4.91)***	0.004(0.06)	0.431(6.25)***
Indirect effect (Sobel)	Indirect eff.	0.039	0.182***	0.215***	0.245***	−0.031	0.179***	0.355***	0.162***
	Std. err.	0.051	0,044	0.043	0.047	0.049	0.046	0.056	0.043
	z-value	0.768	4.159	5.000	5.243	−0.637	3.862	6.344	3.800
	Conf. Interval	−0.060, 0.138	0.096, 0.267	0.131, 0.300	0.154, 0.337	−0.127, 0.065	0.088, 0.270	0.245, 0.464	0.079, 0.246
	RIT	–	41.2%	42.7%	64.3%	–	33.4%	98.8%	27.3%
	RID	–	0.700	0.745	1.804	–	0.502	84.64	0.375
Indirect effect (Monte Carlo)	Indirect eff.	0.042	0.183***	0.216***	0.247***	−0.027	0.181***	0.356***	0.163***
	Std. err.	0.050	0.044	0.043	0.047	0.048	0.046	0.056	0.042
	z-value	0.854	4.209	5.010	5.258	−0.574	3.925	6.314	3.858
	Conf. Interval	−0.054, 0.143	0.096, 0.268	0.130, 0.300	0.152, 0.337	−0.120, 0.067	0.089, 0.272	0.245, 0.462	0.079, 0.246
	RIT	–	41.2%	42.7%	64.3%	–	33.4%	98.8%	27.3%
	RID	–	0.700	0.745	1.804	–	0.502	84.64	0.375

Note: z statistics in parenthesis; * $p < .05$; ** $p < .01$; *** $p < .001$.

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