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Applying the Tier II Construction Management Strategy to Measure the Competency Level among Single and Multiskilled Craft Professionals

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Abstract: Various contemporary studies have revealed a heightened need for the implementation of effective strategies to reduce labor shortages in the construction industry. The subsequent investigation outcomes have identified multiskilling labor strategies as viable solutions to alleviate labor deficiencies in the construction sector. These strategies aim to train single-skilled craft professionals so that they can acquire different skills and complete tasks in addition to their primary duties in the workplace; however, limitations exist in terms of measuring competency levels among single-skilled and multiskilled craft professionals. Thus, a workforce management strategy, referred to as Tier II strategy metrics, is used in this study as a comprehensive approach to evaluate the construction workers' competency levels among more than 2740 workers in the industry. Furthermore, multinomial logistic regression was applied to explain the variability in both the project craft technical and project craft management Tier II score. The overall average Tier II score for multiskilled workers was 6.27, whereas single-skilled workers scored 5.17. The results show that multiskilled craft professionals have higher competency levels compared with single-skilled craft professionals. The outcome from the regression model demonstrates that craft workers who are experts and multiskilled are competent in terms of their project craft technical skill, and years of experience is the most important variable for predicting high competency levels.

Keywords: multiskilling; single-skilled; competency; Tier II

1. Introduction

The construction industry plays a vital role in growing the US economy, accounting for approximately 4.2% of GDP [1]; however, it is widely recognized that the industry is experiencing a long-term shortage of skilled workers, which thus hampers its sustainability and growth [2–4]. According to the Association of General Contractors of America (AGC), 80% of general contractors have experienced difficulties in hiring sufficient craft workers to match the level of demand [5]. Previous research has documented and emphasized the shortage of skilled workers, and consequently, a loss in terms of productivity, growth in hourly wages, an increase in schedules overrunning, a decline in performance quality, and an increase in safety-related incidents in the construction industry [6].

The shortage of skilled labor has emerged as the US construction industry confronts difficulties in finding qualified craft professionals to meet the increased demands for employment in the industry [7,8]. McGraw described the labor shortage in the construction industry in terms of the problems surrounding recruiting and retaining skilled craft workers [9]. In addition to the labor shortage, other employment problems include the lack of craft competency among workers in the current workforce [10]. Existing workers in the construction industry have skill gaps, particularly with regard to soft skills such as communication and leadership, that prevent employees from performing tasks at a higher proficiency level [9,11].

The US construction industry is primarily built upon its highly skilled workforce. It requires individuals to possess a wide-ranging skillset, comprising soft skills, highly technical skills, and the ability to hold specialized roles [11,12]. In addition to possessing a diverse range of skills, workers in the US construction industry are also expected to adapt to rapidly evolving technological advancements, such as the use of drones, automation, and robotics [13]. The required combination of these skills is what makes the US construction industry require a highly skilled workforce [6].

The skillset of construction industry employees is defined in terms of the skilled workers' knowledge, ability, and competence to perform specific tasks effectively in a wide variety of work situations [14,15]. Shah and Burke defined a skill as "an ability to perform a productive task at a certain level of competence" [16]. Nasirian et al. described skill levels in the construction industry in terms of a skillset held by workers that is at a level desired by the employer [14]. Within the construction industry, a skilled craft project is typically carried out by someone who works as a team leader and who utilizes their expertise in order to plan and execute the work in accordance with their independent judgement, while also overseeing and supervising team members [17].

Technical, socioemotional, practical, and cognitive skills, for example, have been identified as important skills that are required in the construction industry as they increase competency among craft professionals [18]. These skills are needed for the survival and growth of the workforce in the construction industry [19]. Some of these skills require a certain set of competencies in order to enhance workforce efficiency on site [20].

Craft competency refers to an individual's ability to perform tasks that result in effective and excellent work performances when undertaking a job [21]; however, an individual's competency, traditionally, is dependent on the organization's work culture [22], a process of continuous improvements, as well as the individual's measurable knowledge and skills [23]. These craft skillsets are distinguished from others by their perceived desirability in the construction industry [24]. Authors previously distinguished between craft skills and craft competencies by defining a craft skill as the ability of individuals to make use of specific tools for an intended purpose; this allows them to perform a specific task. Conversely, competency is defined in terms of the abilities, commitments, knowledge, and skills that enable individuals to perform jobs effectively in a wide range of working situations [15,17].

Recent studies comprehensively reviewed more than 260 articles to identify desirable skillsets among construction professionals. These studies found 72 skills that came together to form major competencies needed in the current construction industry market [19]. Among the identified 72 skills, organization, technical skills, human relations, communication, personnel management, and operational planning were identified as the most valuable skills in the construction industry, which is currently experiencing labor shortages [24]. The construction workforce may acquire some of these skills as they become more experienced; in other words, individuals in the workforce accumulate and develop these skills over time [25]. However, a gap exists between the workforce and the acquisition of these skills; this is attributed to the low competency level of workers [17].

To effectively enhance the competencies of construction craft workers, several training programs have been implemented using different strategies, resulting in improving the practical skills of the trainees [18]. These programs are generally associated with higher labor costs and training expenditures [26]. The multiskilling strategy is an alternative and appropriate solution to fill the skills gap and enhance competency levels [2,27]. According to scholars of strategic human resource management, the multiskilling strategy was introduced to the construction industry as a labor practice to build core competencies among craft professionals [28]. In general, the core competencies of multiskilled craft workers differ from one another [17]. These core competencies consist of skill sets that are developed through a variety of techniques that make multiskilled craft professionals capable of performing a variety of tasks [29]. They also consist of proficiency levels that measure the extent to which the individual is skilled in his or her craft [30]. Multiskilled craft workers are trained in multiple skills and competencies so they may master one or more skills in addition to their core competency skill [31,32]. However, a limitation in the existing literature is the absence of an examination of the impact of multiskilling strategies on craft competency. This paper will focus on measuring the ability of the multiskilling strategy to enhance craft professionals' competency in the construction industry. The Tier II strategy was developed to provide a structure for a long-term evaluation on an improved workforce [33]. The strategy could assess the workforce competency by measuring different skill levels identified by Tier II [34]. Subsequently, a survey was designed based on the Tier II workforce management strategy and administered among the U.S. construction industry workforce. The main objective of the paper is to determine if the multiskilling strategy could enhance an individual's competency in the construction industry. To address this primary objective, two secondary objectives emerge: (1) compare the strategy metrics in two Tier II components—craft technical and management skills between single-skilled and multiskilled individuals; and (2) explain the variability in both the project craft technical and project craft management Tier II score.

To achieve the research objective, authors applied the Tier II workforce management strategy to measure the degree to which project craft technical, and project craft management skills can be adopted by single-skilled and multi-skilled craft professionals.

This study contributes to the existing literature by providing new insights into how the multiskilling strategy may affect individual competency levels, which can help to improve and promote the multiskilling strategy and identify skill gaps among current US construction workforce. The findings, therefore, can be relevant to a variety of stakeholders, including the construction industry workforce, companies, and training providers, especially in a long-term training system. By identifying the key competencies among individuals, the study can help to improve the overall competency level of the construction industry workforce, thus potentially leading to more qualified workers.

2. Literature Review

The US construction industry is one of the most labor-intensive industries, and thus, it requires a coherent, motivated, and healthy workforce that is highly skilled and competent [6,35]. A competent workforce that possesses advanced technical skills, experience, and higher intellectual abilities, contributes considerably to the competitive advantage of a company [36,37]. Human resources, therefore, are required to meet industry needs by recruiting, selecting, and orienting qualified craft workers to maintain and sustain the construction industry [38]. However, the construction industry is facing shortages of labor, mainly among the highly skilled and competent trades, which presents major challenges for human resource planners in the construction industry [12,37].

The shortage of skilled labor encourages employers in the construction industry to adopt strategies that bring more flexibility in workforce management [37]. Previous researchers defined workforce flexibility in two ways [39]. First, from the organization's perspective, workforce flexibility is defined as the organization's ability to adopt new practices which lead to changes in the work environment [40]. Second, from the worker's perspective, workforce flexibility is defined as an individual's ability to make choices by arranging core aspects that meet his or her personal needs [39]. According to Qin et al., there are five main strategies that could help to achieve workforce flexibility: flexible working hours, teamwork, floater plans, resource allocation, and a multiskilled workforce [41]. The multiskilling and cross-training strategy has been proposed as a reformative labor practice. These practices aim to increase the flexibility of the craft professionals by training workers in multiple skills, which would thus increase their competency levels [32,42]. Reportedly, the multiskilling strategy significantly benefits both organizations and individuals in the construction industry [43]. Multiskilling strategies can develop workforce competency as well as continuously utilize the workers' capabilities throughout construction projects [44].

In the construction industry, a flexible workforce performs different tasks and functions at different competency levels due to fluctuations in both product demands and labor resources [45]. Johari et al. identified the essential and desirable competencies for a skilled construction workforce and found that attitude, motivation, health/physical strength, reading and writing skills, mathematical skills, and problem-solving skills were found to be significant essential competencies, while aptitude, listening skills, and working experience were the most desirable competencies [17]. These skill competencies should be measurable and countable in order to differentiate between competent and incompetent individuals [46]. Therefore, the Center for Construction Industry Studies (CCIS) at The University of Texas at Austin proposed the Tier II workforce management strategy to evaluate skill levels among workers in the construction industry [33]. The strategy was also designed to measure the competency level among the construction industry workforce [34]. In the context of the Tier II strategy, the multiskilling strategy can increase workforce flexibility by reducing the demand for labor [47]. However, previous research has not measured the impact of the multiskilling strategy on workforce competency, especially among multiskilled labors.

Three main considerations in the literature review, including workforce competency, multiskilling, and the Tier II strategy, are described in the following sections.

2.1. Workforce Competency

In most leading economies, the concept of workforce competency is commonly perceived and prioritized as a critical factor for economic growth [48]. For example, research conducted in New Zealand indicates that although the construction industry is one of the biggest employment sectors, it is currently facing a significant labor shortage, thus affecting the competitiveness of its construction workforce [49]. Regarding the UK construction sector, many companies are struggling with the challenge of retraining their workforce to adapt to new technologies or working methods due to a lack of skilled and competent workers [50]. Within the US construction industry, the US ranks third globally in terms of workforce competitiveness, behind Switzerland and Singapore [51]. Competency-modeling approaches that evolved from the original work of David McClelland in the late 1860s were proposed as effective models to identify the variables that predict successful job performance [52]. In 1998, Marrelli defined competencies as measurable individual abilities, commitments, knowledge, and skills that are required for effective work performance [53]. The term competency was broadly introduced to the management field by Boyatzis, who first introduced the "Job Competence Assessment" method in the USA [54]. Spencer and Spencer expanded on this definition to include "a motive, trait, skill, aspect of one's self-image or social role, or a body of knowledge which he or she uses" [54,55]. In the late 1990s, the concept of competency has been studied and investigated by many researchers who later developed several competency models to analyze the performance of construction workers [17].

The study of workforce competency has been extended by numerous researchers to measure the impact of competent and incompetent workers' activities in the construction industry. Durdyev et al. applied the structural equation model to identify the factors affecting construction labor productivity and they found a significant correlation between individuals' competency and enhancing labor productivity in the construction industry [10]. Heravi and Eslamdoost proposed a predictive model for estimating construction workforce productivity [56]. They discovered that by enhancing "workforce competence," workforce productivity could be increased by 13–18.7%, which makes it one of the most influential elements that can significantly improve labor productivity. In addition to productivity, workforce competency also plays a significant role in achieving a positive safety climate [57] and improved work performance in the construction jobsite [58], which leads to lower labor cost, and higher project quality [59]. Dai et al. identified superintendent competency and foreperson competency to be among the most influential factors that were related to construction industry workforce issues [60]. The most recent study by Johari et al. reported that higher competencies among the construction workforce can produce an effective and efficient work performance at the jobsite [17].

Several studies have been conducted in the past to develop models that measure the workforce competency level within the construction industry. Manoharan et al. focused on individuals' competencies (KSAs) which are measurable; this included the level of significant knowledge, skills, and abilities that are required by the workers for effective work performance and for developing a labor training guide model that enhances the productivity and performance of a workforce in the construction industry [58]. In 2019, the Employment and Training Administration (ETA) collaborated with the Associated General Contractors of America (AGC) to promote a safe and skilled workforce with a program for developing higher competency levels and skillsets using models that are essential for educating and training a globally competitive workforce. This demonstrated that competencies are necessary for workers to enhance their efficiency at the jobsite [17].

2.2. Multiskilling Strategy

In recent years, the skilled labor shortage is considered to be the most critical issue facing the construction industry [3]. It is one of the major restraints on workforce productivity [61]. Multiskilling or cross-training has been proposed by the Construction Industry Institute (CII) and the Centre for Construction Industry Studies as one possible solution to reduce a shortage of skilled craft workers [44]. The multiskilling strategy refers to the training of the workforce in order to acquire different skills and tasks in different trades, in addition to their primary trade in the workplace [62]. The strategy brought more flexibility to human resources by assigning different tasks to workers during projects, which resulted in the alleviation of the skilled labor shortage problem [37]. Multiskilled crafts may have a primary trade where they are certified and highly competent, but their work is not limited to that trade [42].

The main motivation for introducing the multiskilling strategy to the construction industry was to enhance productivity and deal with workforce shortages [44]. The strategy has contributed to the construction industry's development by reducing the lack of skilled labor [44,63,64], minimizing construction costs [44], increasing flexible staff deployment [41,64,65], improving onsite safety [37], and improving project quality [64].

The multiskilling strategy was introduced to the construction industry as a managerial strategy to develop competency within the workforce [44]. Duray addressed managerial issues through a survey and found that if workers were competent and multiskilled, this led to more flexibility in the workforce [27]. However, Gomar et al. believed that the benefits of multiskilling became insignificant after craft workers performed work in more than two trades [66]. Regardless, it is noteworthy to observe the impact of the multiskilling strategy on workforce competency.

2.3. The Tier II Workforce Management Strategy

Previous research has shed light on desirable skill levels among construction workforces. Construction workers are required to possess certain skill levels, defined as competencies, and these include, but are not limited to, problem-solving, communication, experience, people management, project management, and general computer skills [67]. The Tier II workforce management strategy will be applied in this paper to measure the presence of these skills among workforces in the construction industry.

The Tier II workforce management strategy was introduced to the construction industry as a comprehensive method that formed part of a two-tier strategy that was proposed by the Center for Construction Industry Studies (CCIS) and the Construction Industry Institute (CII) [34]. The purpose of the Tier II strategy was to provide a structure for the long-term evaluation of workers, which could thus create an improved workforce [33]. Additionally, the Tier II strategy was adopted as a cohesive way of maximizing the utilization of the existing construction workforce, and to assess the potential impact of the lack of skilled construction labor by evaluating solutions to the problems of training, career paths, and wages in the industry [68]. The strategy also could measure the competency levels among the construction industry workforce [34].

The Tier II strategy is concentrated on the utilization of fewer, well-educated, and highly qualified craft professionals who also perform lower-management functions in addition to their primary duties in the workplace [69]. A key advantage of the strategy is to minimize construction cost, improve safety, improve project quality, and enhance both project schedules and productivity [34].

The characteristics of the Tier II workforce strategy is defined by metrics that measure the degree of implementation of the five index components: Project Craft Technical Skills, Project Craft Management Skills, Information Technology Utilization, Craft Utilization, and Organization, as shown in Table 1. The maximum score for each component is 100 points, and when divided by 50, it results in a maximum potential index score of 2.0 points per index component. Therefore, the Tier II Project Index can be calculated by adding up the scores of all five components. Forty percent of the Tier II Project Index score is composed of project craft technical skills and project craft management skill components, which are the two components that were included in this study.

Table 1. Components and Elements of Tier II Metric [69].

Components	Elements
Craft Technical Skills	Craft Certifications Technical Experience Continuous Training and Education
Craft Management Skill	Administrative Computer Planning Job Management Work Record
Information Technology Utilization	Integrated Information Access Hardware
Craft Utilization	Crew Mix Use of Multiskilled Workers
Organization	Communications High-Performance Workplace

In 2005, Castañeda et al. indicated that the Tier II strategy metrics are feasible and achievable in assessing the proficiency of construction workers with regard to the skills proposed by the Tier II strategy [34]. In the Tier II matrix, proficiency is defined as a skill that renders workers competent and capable with little or no supervision [70].

3. Research Methods

The study presented in this paper comprised both exploratory and explanatory research, which focused on assessing and describing the current competencies of the construction industry workforce among multiskilled and single-skilled workers.

3.1. Research Design

3.1.1. Tier II Strategy Metrics

The first objective of this study was to investigate if the multiskilling strategy can enhance individual's competency level. To achieve the research objective, a workforce management strategy, referred to as Tier II strategy metrics, is used in this study as a comprehensive approach to evaluate the construction workers' competency levels from a sample that included data from over 2700 responses from all 50 states. The survey received the highest contributions from states with large populations, which included New York, California, Texas, Pennsylvania, and Illinois.

The research objective was to compare the strategy metrics in two Tier II components—craft technical and management skills. These components mainly rely on individual skills, whereas the remaining elements are functions of the organization's structure. Every component in the Tier II metric has elements and evaluation criteria.

The analysis of workers' Tier II skills focuses on the average score for each particular element of the Tier II workers' skills for both multiskilled and single-skilled craft professionals. Hence, participants were asked to indicate if they were multiskilled or single-skilled. The goals were to identify the areas in which survey participants have some Tier II skills and to identify their competency levels in these areas.

Each component of the metric has a measurement system and evaluation criteria, resulting in a score of 0, 5, or 10. The three components comprise different elements that constitute its metrics.

The craft technical metric consists of three elements: craft certification, technical experience, and continuous training and education. To earn a 10 on the craft certification evaluation scale, craft professionals must be certified in at least three crafts in addition to their primary craft. Table 2 summarizes the principal elements of the three categories of the craft technical Tier II workforce strategy.

Table 2. Tier II project craft technical skill evaluation criteria [69].

Elements	Evaluation Criteria	Score
Craft certification	Certified in three crafts	10
	Certified in two crafts	5
	No certification	0
Technical experience	More than ten years of experience at the certified craft level	10
	Five years of experience at the certified craft level	5
	Less than one year of experience at the certified craft level	0
Continuous training and education	More than 200 h of training and skill updating in the last three years	10
	100 h of training and skill updating in the last three years	5
	No training or skill updating since first craft certification	0

Table 3 shows the score for an individual's management skills in administration, computer operation, planning, job management, and overall work. The administrative element includes organizing and coordinating activities, managing resources, prioritizing tasks, and communicating effectively with others. Computer skills assess the individual's ability to use computer hardware and software, such as Building Information Modeling, at the worksite. Planning skills refer to the range of an individual's abilities related to using materials, equipment, tools, information requests, short-term planning, and scheduling. Job management skills refer to the combined hours of training that the individual has completed with regard to developing their job management skills, such as crew coordination, inter- and intra-craft coordination, selecting work packages, and leadership. Finally, the work record is a personal performance measurement that includes safety, attendance, quality, productivity, and initiative on the job.

Once the average score for each particular element was assessed and described, authors applied the *t*-test to determine if differences between the average score for multiskilled and single-skilled crafts, regarding the Tier II strategy metric elements, were statistically significant.

Table 3. Tier II project craft management skill evaluation criteria [69].

Elements	Evaluation Criteria	Score
Administrative	Certified in at least four administrative skills	10
	Certified in two administrative skills	5
	No certification in administrative skills	0
Computer	Certified in at least four computer skills	10
	Certified in two computer skills	5
	No certification in computer skills	0
Planning	Certified in planning skills	10
	One-hundred and sixty hours of training but not certified in planning skills	5
	No training or certifications	0
Job management	Certified in job management	10
	One-hundred and sixty hours of training but not certified in job management	5
	No training or certifications	0
Work record	Superior in all categories	10
	Superior in some categories, modest in others	5
	Weak in most categories	0

3.1.2. Multinomial Logistic Regression

To address the second objective of the paper, multinominal logistic regression was used to identify key potential factors that may contribute to differences in the level of competency among single-skilled and multiskilled individuals. The Tier II elements—craft technical and management skill components—were included in the MLR model as dependent variables, as listed in Table 4. Six explanatory variables identified in the previous literature were included in the MLR model as independent variables [12,46,64,71,72].

Table 4. Explanatory variables.

Variables	Description
Dependent	
Craft certification Technical experience Administrative Computer Planning Job management Work record	Tier II workforce management measured using scores of 0, 5, or 10
Independent	
Age	Craft age
Years of experience	Years of experience at the certified craft level
Number of certifications	Number of certified trades
Craft training experience	1—Yes, 2—No
Education level	1—Less than high school, 2—High school, 3—More than high school
Work Position	1—Foreperson, 2—Craftsperson/journeyperson, 3—Apprentice/helper

MLR models are appropriate when the predicted (dependent) variables have classifications and the response (independent) variables are discrete [73]. It is an extension of binary logistic regression, which is typically used to compare the likelihood of an occurrence of a particular value of a response with the likelihood of an occurrence of the reference value in the response [74]. In the current study, the reference value is the maximum possible score in the Tier II matrix (i.e., 10), which indicates the best competency rating.

The multinomial logistic regression model can be expressed using Equation (1):

$$Y = \frac{e^{(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k)}}{1+e^{(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k)}} \tag{1}$$

where X_k is the response (independent) variable, β_0 is the intercept, and β_1 is the logistic slope (beta coefficient).

3.2. Survey Design and Structure

A web-based survey of US construction workers was conducted to obtain the data for inputting into the Tier II worker metrics. This questionnaire gathered data regarding the background and characteristics of the workers, including their competency levels that were related to the Tier's matrix elements. In this study, based on a review of the Tier II metric elements, and a workshop discussion among industry experts on the construction workforce, survey questions were developed to gather data on a range of topics, including personal characteristics such as age, marital status, education, and work experience. These individuals' characteristics were identified previously in construction industry research [75].

As the Tier II worker metrics were proposed to the construction industry around 20 years ago, the authors updated the information, equipment, materials, technologies, and skills before releasing the survey to the construction professionals, mainly to account for the new technological tools being used on current sites. Among other questions, the survey asked construction workers if they were certified in more than one trade to indicate if they are multiskilled workers.

3.3. Data Collection

The survey was administered and designed through the online software, Qualtrics, in 2020 to decrease subjectivity when computing the Tier II project index. The survey was sent to construction companies and industry leaders for distribution across the US construction workforce. Construction companies and industry leaders distributed the survey in 2020 by using an anonymous link. In order to select a sample of construction workers that was representative of the industry, the survey was sent to companies and industry leaders that were undertaking different types of construction projects. Both the union and open shop project were included in the survey. Moreover, the survey was focused on onsite craftsperson and frontline supervisors (foreman and general foreman) to ensure the sample was representative. Once the data was received, Microsoft Excel 2019 and SPSS v28.0 were used to clean and analyze the data.

A total of 2740 responses from all 50 states were received, as shown in Figure 1. Among those responses, 94.7% were male, 5.1% were female, and 0.3% identified with another gender. In addition, only 3% were under 25 years, whereas 16.8% were between 25 and 34 years. Finally, a quarter of the responses were in the age groups of 35–44 and 45–54, whereas the remaining 29.5% were 55 or older.

Figure 1 shows the geographic distribution of the survey participants. Each dot indicates the location of participants in the survey. A high number of responses were concentrated around urban areas.

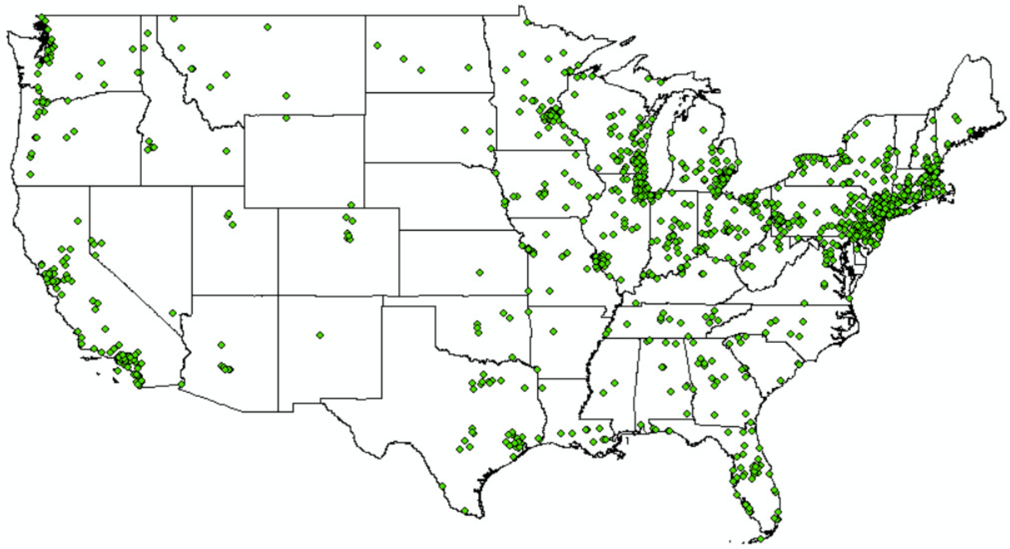


Figure 1. Geographic distribution of RT-370 craft survey responses.

As shown in Figure 2, which presents the distribution of respondents based on education level, 31% had attended some college but did not hold a degree, whereas 22% finished high school.

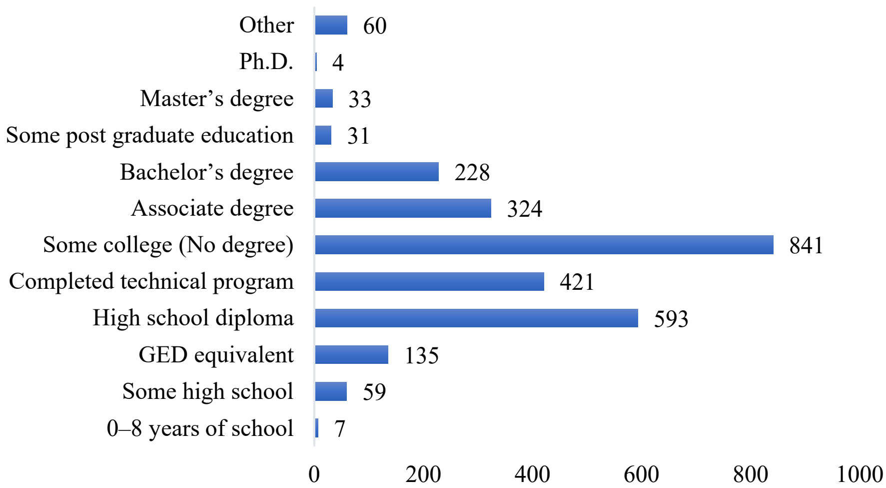


Figure 2. Distribution of respondents based on education level.

As shown in Figure 3, the RT-370 craft survey shows that the highest percentage of respondents (41%) were craftspersons or journeypersons, whereas forepersons and apprentices/helpers represented the second-highest number of responses by job title at 14%. This research focuses on onsite craftspersons and frontline supervisors (forepersons and general forepersons) in the US construction industry. Therefore, managerial positions are excluded from the analysis.

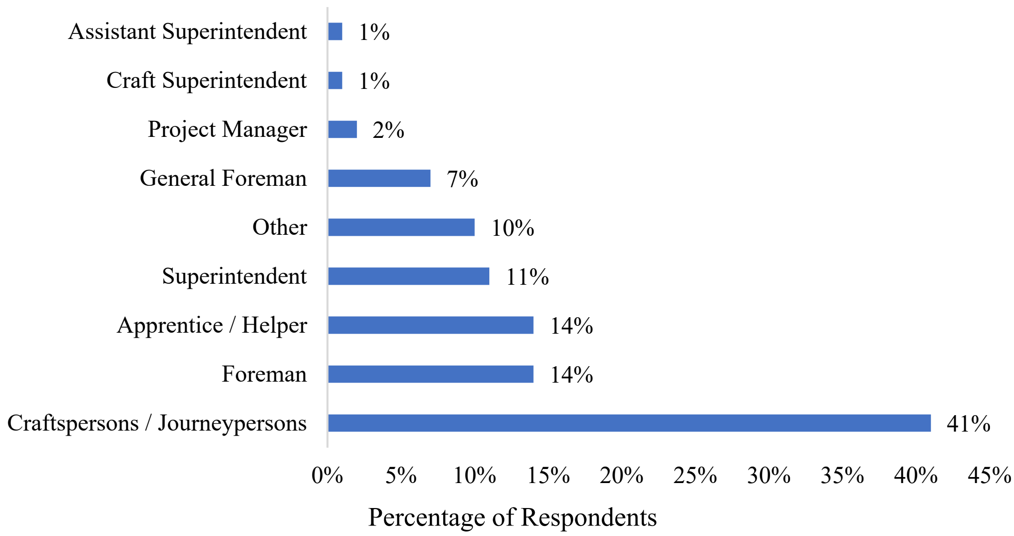


Figure 3. Number of responses by job title (RT-370, 2021).

3.4. Data Analysis

To test the reliability and validity of the survey, Cronbach's alpha was measured to assess the internal consistency of the survey data. The overall Cronbach's alpha for the survey was found to be 0.735, which is above the cut-off limit of 0.7 [76].

3.4.1. Tier II Strategy Metrics

To check the consistency of the result, The Tier II element scores were measured for the general population of the construction industry based on two criteria: overall multiskilled craft professionals vs. overall single-skilled craft professionals; and multiskilled craft professionals vs. overall single-skilled craft professionals, based on the individual's primary craft. As most of the respondents belonged to the carpentry craft, the authors only applied the analysis to the carpentry trade.

The *t*-test was used to compare the Tier II score means of the independent group to determine whether there is a statistically significant difference between the mean score of single-skilled workers and multiskilled workers. Even though the sample size of the two groups is different, the *t*-test is still can be used. For this test to be valid, it is assumed that the two groups have the same variance and that the samples are selected from distributions that follow a normal pattern. However, the test demonstrates a high level of resistance to unequal variances.

3.4.2. Multinomial Logistic Regression

Before the MLR was employed in the dataset, some assumptions were evaluated. First, the dependent variable should be determined as nominal, which, in our case, is either 0, 5, or 10. Next, one or more independent variables must be continuous, ordinal, or normal (age, years of experience, and the number of certifications are continuous variables; education level, work position, and training are nominal variables). Multicollinearity variables and outliers are examined separately in the next section.

- Multicollinearity Assessments

Multicollinearity occurs when either the predictors are interdependent or a strong relationship exists between them, which can lead to the overfitting of model responses [77]. To detect the degree of collinearity in the dataset, the variance inflation factor (*VIF*) was measured. The *VIF* was calculated for each potential variable using Equation (2):

$$VIF_i = \frac{1}{1 - R_i^2} \quad (2)$$

where R_i^2 is the coefficient of multiple determination.

Any *VIF* of and greater may indicate the presence of multicollinearity, where a value of 4 is recognized as a conservative value [78]. After measuring the *VIF* for the whole model, none of the variables exceeded a value of 4, thus eliminating the concern of multicollinearity.

- Outliers

Regression models are usually sensitive to outliers and high leverage values. Therefore, outliers among the data are identified and removed before running the MLR. Age and the number of experiences were the variables that carried outliers in their data. The authors assessed the outliers by plotting the residuals (the difference between the observed and predicted values) and they identified any data that were significantly different from the rest. Of 2740 responses, 22 outliers were excluded.

Due to their high leverage values, the number of certification variables in the craft certification element, and the years of experience variable in the technical experience element, were dropped from the MLR model. This helped eliminate the potential risk of inappropriate observations.

However, limitations exist when using MLR. The model assumes linearity in the relationship between the dependent variables and the independent variable, which may result in inaccurate prediction results [79].

4. Result of Analysis

4.1. Tier II Element Score Results

A total of 980 craft professionals were identified as single-skilled, whereas 719 were identified as multiskilled craft professionals on the RT-370 craft survey. The analysis of a craftsperson's receptiveness to the Tier II element scores was conducted by first measuring the average score of each element of Tier II between single-skilled and multiskilled craft professionals among the general population of the industrial construction workforce.

The matrix was modified to include new evaluation criteria for the craft certification element because the existing method was not effective in identifying individuals who were certified in at least one trade. To address this, the authors scored individuals a 3 if they were certified in at least one trade. The matrix scale ranged from 1 to 10, with 0, 5, and 10 given as possible values. Given that a score of 2.5 is halfway between 0 and 5, the authors chose number 3 to be more conservative. The purpose of modifying evaluation criteria for the craft certification element in the matrix is to distinguish between the single-skilled and multiskilled workforce. The evaluation criteria without modifications were given a score of 0 for crafts which are not certified in any trade, and 5 for crafts which were certified in at least two trades. However, it was difficult to track single-skilled workers who are certified in at least one trade in this evaluation criteria. After consulting with workforce experts, authors added the new evaluation criteria to provide more levels of granularity than the original scale in this situation. The maximum score for each element of Tier II is 10, which indicates the highest competency level a craftsperson could achieve; therefore, subtracting the average score of the Tier II skills from the maximum score in each element equals the opportunity for competency improvement in each skill.

As shown in Figure 4, the results show higher average scores in the Tier II skills among multiskilled rather than single-skilled craft professionals in all project craft technical and management skills, except the planning element. The *t*-test revealed statistically significant differences between multiskilled and single-skilled worker receptiveness in craft certification technical experience, continuous training and education, and administrative, computer, planning, and job management skills as shown in Appendix A. However, no significant difference was found in the work record skill level between the two groups. The craft certification element scored the highest Tier II competency score among the multiskilled individuals, whereas the planning element scored the highest competency score among the single-skilled individuals. Notably, planning was the only element where single-skilled workers scored higher than multiskilled workers. Both single-skilled and multiskilled individuals demonstrated a low competency level in the work record element.

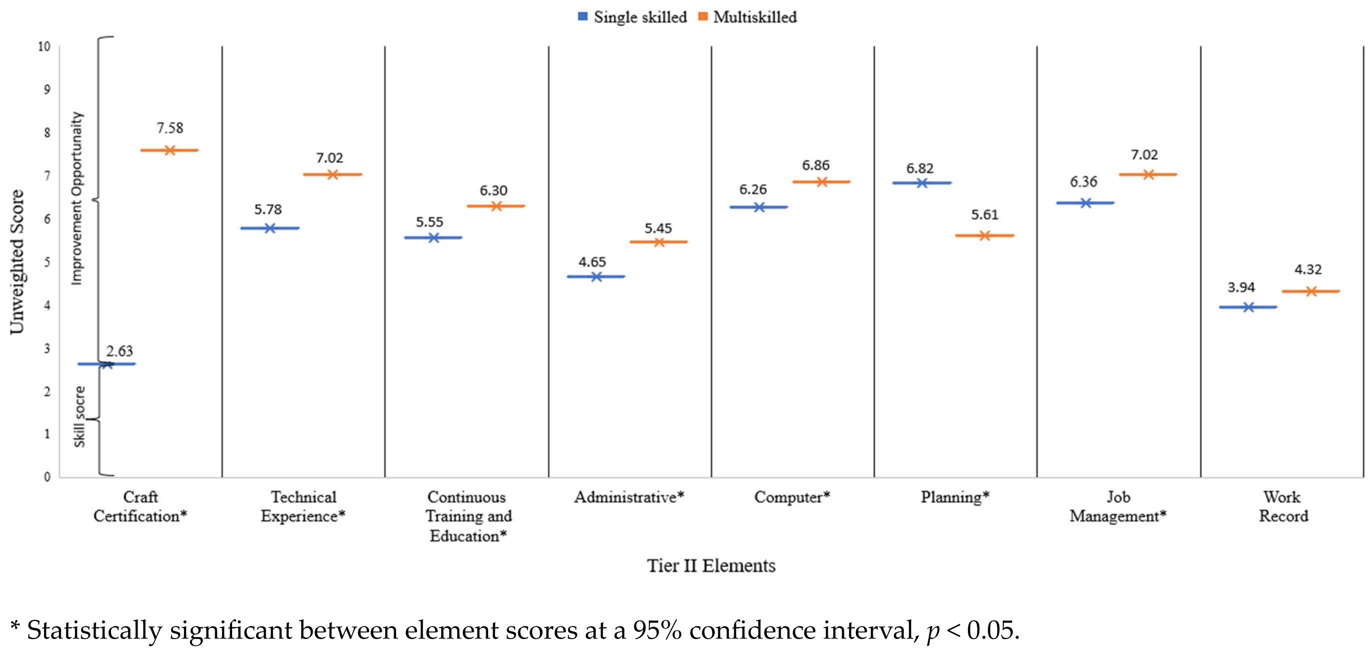


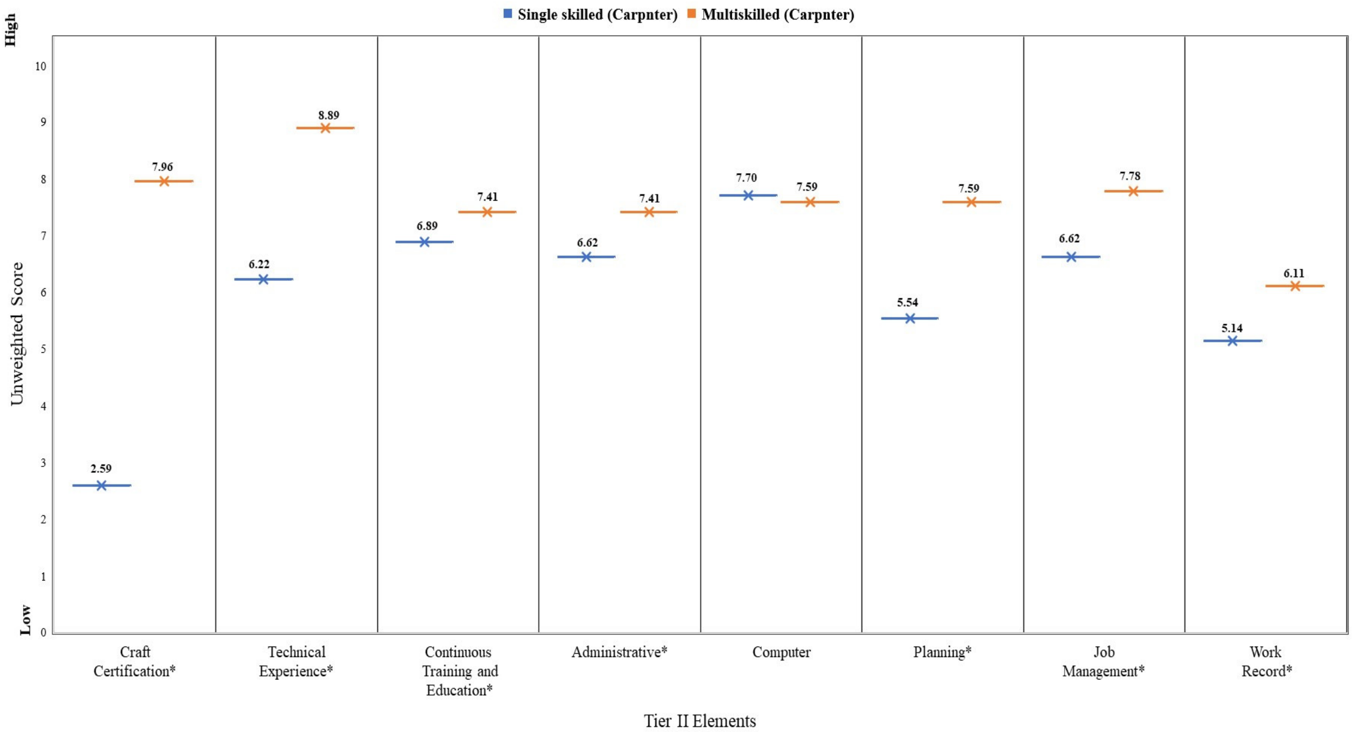
Figure 4. Tier II element scores based on the overall multiskilled craft professionals vs. overall single-skilled craft professionals.

The study results also indicate that opportunities for improvement exist in each skill among craft professionals. The findings show that the improvement values for multiskilled and single-skilled craft professionals, respectively, are 2.42 and 7.37 for the craft certification element, 2.98 and 4.22 for the technical experience element, 3.70 and 4.45 for the continuous training and education element, 4.55 and 5.35 for the administrative element, 3.14 and 3.74 for the computer element, 4.39 and 3.18 for the planning element, 2.98 and 3.64 for the job management element, and 5.68 and 6.06 for the work record element.

According to the results in Figure 4, multiskilled craft professionals exhibit higher competency levels than single-skilled craft professionals in most of the Tier II elements. At the same time, the analysis suggests that more room for improvement exists in the competency levels among single-skilled workers. However, measuring the desired competency level for each skill is not addressed in this investigation.

The authors assessed the consistency of the Tier II competency level results by conducting the same analysis for the carpentry craft. As the carpenter union helped distribute the survey, the carpenter craft is represented by the highest percentage of respondents as per the RT-370 craft survey results. Carpentry is the only trade included in this investigation. The other trades were excluded because of the small sample size; a larger sample size may be necessary to achieve sufficient statistical power.

Some intriguing similarities are observed in Tier II scoring among multiskilled and single-skilled craft professionals in carpentry. The results show that multiskilled craft professionals scored higher in most Tier II elements; however, not all the elements show statistically significant differences in terms of multiskilled and single-skilled carpenters' receptiveness to Tier II skills. The *t*-test revealed statistically significant differences between multiskilled and single-skilled carpentry worker receptiveness in craft certification technical experience, continuous training and education, administrative, planning, job management skills, and work record skills. Multiskilled carpentry crafts earned higher competency scores than single-skilled individuals in all Tier II elements except computer skill as shown in Figure 5.



* Statistically significant element scores at a 95% confidence interval, $p < 0.05$

Figure 5. Tier II score based on an individual's primary craft (carpentry).

After analyzing the competency levels of RT-370 craft participants, using the Tier II workforce strategy as a comprehensive evaluation method, multiskilled craft professionals are considered to have higher competency levels than single-skilled workers in the overall population. To explain the variability and better understand the influence of the Tier II score on the results, the research team applied a regression model to explain the relationship between the dependent and independent variables and how they contribute to the variability in the results.

4.2. Multinomial Logistic Regression Result

The authors conducted an MLR analysis after ensuring that all assumptions were valid. The analysis was run for each of the three categorical dependent variables (i.e., craft certification, technical experience, and continuous training and education), meaning each dependent variable was evaluated in a separate analysis. The full analysis of the MLR for each element will be shown in Appendix A.

The significance and fit of the MLR models for the project craft technical skills are shown in Table 5. For all three elements, the chi-square values were highly significant, thus indicating a proper fit for the MLR model. The analysis in SPSS software reported three R^2 measures: Nagelkerke, Cox and Snell, and McFadden. However, statistics experts suggest that the Nagelkerke R^2 value is the most reasonable value to use [74]. The Nagelkerke R^2 value was 40% for craft certification, 50% for technical experience, and 17% for continuous training and education, thus indicating acceptable model performance [80]. The Nagelkerke R^2 value represents the amount of variability in the dependent variable that can be accounted for by the independent variable(s) in the model [81]. For example, a Nagelkerke R^2 value of 50% indicates the proportion of variation explained by the model in this study. However, it is important to note that there is no universally accepted threshold for an acceptable Nagelkerke R^2 value; therefore, a higher Nagelkerke R^2 value indicates a better fit of the model [82].

Table 5. Significance and fit of the MLR model for craft technical skills.

Project Craft Technical Element	Chi-Square Statics	Degree of Freedom	Significance Level
Craft Certification	142.62	14	0.001
Technical Experience	350.71	14	0.001
Continuous Training and Education	90.75	16	0.001

With three dependent-variable craft certification Tier II scores (0, 5, 10), the regression model was conducted to see which independent variables had significant effects on the Tier II scores. The significance level of the parameters in an MLR model was obtained from the Wald test by dividing the coefficient β by its standard error and then squaring the result [73]. Of all the independent variables, years of experience, receiving craft training, and work position were significant at level 0.00 in craft certification elements.

In the MLR model, both the coefficient β and exp(β) are important to assess the impact of the independent variable(s) on the dependent variable's outcome [74]. To explain coefficient β and exp(β), for example, an exp(β) of 0.795 represents a 0.229 unit decrease, which means that for every unit added to the years of experience, the likelihood of a Tier II score of 0 decreases by 0.299. In other words, a negative β indicates that any increase in years of experience significantly decreases the likelihood of the Tier II score being 0 as shown in Table 6. Furthermore, an exp(β) of 4.292 represents a 1.457 unit increase, meaning for every unit added to receiving no training, the likelihood of the Tier II score being equal to 0 (not certified in the craft), rather than level 10, increases by 1.475 units. For a craftsperson/journeyperson, an exp(β) of 0.105 represents a 2.255 unit decrease, which means that for every unit added to craftsperson/journeyperson, the likelihood of a Tier II score of 0, rather than 10, decreases by a factor of 2.255.

Table 6. Parameter estimates of the MLR for craft certification skills.

Craft Certification		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	Odds Ratio, Exp(β)	Log of Odds Ratio, β	Odds Ratio, Exp(β)
Intercept		1.727 *		0.616	
Age		−0.015	0.985	0.001	1.001
Years of experience		−0.229 *	0.795 *	−0.035	0.965
Craft training experience	-NO	1.457 *	4.292 *	−0.243	0.784
	-YES	0	0	0	0
Education level	Less than high school	−0.43	0.958	−0.727	0.483
	High school	0.227	1.255	0.046	1.047
	More than high school	0	0	0	0
Work Position	Foreperson	−0.664	0.515	−0.061	0.941
	Craftsperson/journeyperson	−2.255 *	0.105 *	−0.277	0.758
	Apprentice/helper	0	0	0	0

The reference category: Craft Certification at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

The results suggest that years of experience and being a craftsperson/journeyperson had negative associations, whereas receiving training had positive associations, with the likelihood of the craft being at a lower competency level (non-certified craft) rather than a higher competency level (certified in at least three trades). Of note, all of the above results were compared against a competency level of 10; these results assumed that all other predictors were held constant, and only the effect of one predictor was being considered at a time.

As shown in Table 7, for the "technical experience" dependent variable, age, the number of certifications, and work position were found to be significant variables at $p < 0.05$. As the age and the number of certifications increased by one unit, the probability (odds ratio) of a Tier II score of 0, compared with a Tier II score of 10, decreased by a factor of 0.90 or 0.724, respectively. In other words, as age or the number of certifications increases, the likelihood of the craft being at a lower competency level (not certified), rather than a higher competency level (certified in at least three trades), decreases. Additionally, as age increases by one unit, the probability of a Tier II score of 5, compared with a Tier II score of 10, is reduced by a factor of 0.96.

Table 7. Parameter estimates of the MLR for technical experience skills.

Technical Experience		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	Odds Ratio, Exp(β)	Log of Odds Ratio, β	Odds Ratio, Exp(β)
Intercept		6.769 *		5.331 *	
Age		−0.104 *	0.901 *	−0.088 *	0.961 *
Number of certified trades		−0.324 *	0.724 *	−0.036	0.964
Craft training experience	-NO	0.392	1.480	−0.206	0.813
	-YES	0	0	0	0
Education level	Less than high school	−0.688	0.502	−1.189	0.305
	High school	−0.431	0.650	−0.073	0.929
	More than high school	0	0	0	0
Work Position	Foreperson	−5.054 *	0.006 *	−3.003 *	0.050 *
	Craftsperson/journeyperson	−3.692 *	0.025 *	−2.182 *	0.113 *
	Apprentice/helper	0	0	0	0

The reference category: Technical Experience at a score of 10; * Statistically significant at a 95% confidence interval, $p < 0.05$.

We can hold both age and the number of certifications constant and consider only the significant categorical variable, which is the work position. In this case, the likelihood of participants working as forepersons or craftspersons/journeypersons, and scoring a 5 (i.e., five years of experience at the certified craft level) rather than 10 (i.e., ten years of experience), are 0.006 or 0.025 times, respectively, when compared with individuals who are apprentices/helpers. Similarly, the odds of participants working as forepersons or craftspersons/journeypersons achieving a score of 0 (less than one year of experience), rather than 10, are 0.050 or 0.113 times, respectively, when compared with individuals who are apprentices/helpers. Thus, individuals who are forepersons or craftspersons/journeypersons are less likely to have lower competency levels when compared with apprentices/helpers.

With a 95% confidence level, the result in Table 8 indicates that for the "continuous training and education" dependent variable, the number of certified trades, years of experience, and work position were found to be significant independent variables. As the number of certifications across different trades increases by one unit, the probability of a Tier II score being 0 rather than 10 decreases by a factor of 0.508. Hence, workers certified in more trades are more likely to spend more time training and in education.

Table 8. Parameter estimates of the MLR for continuous training and education skills.

Continuous Training and Education		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	Odds Ratio, Exp(β)	Log of Odds Ratio, β	Odds Ratio, Exp(β)
Intercept		−2.414 *		−1.883 *	
Age		0.016	1.017	0.022	1.022
Number of certified trades		−0.678 *	0.508 *	−0.126	0.881
Years of experience		0.086 *	1.089 *	0.053 *	1.054 *
Craft training experience	-NO	−1.595	0.203	−0.292	0.746
	-YES	0	0	0	0
Education level	Less than high school	1.267	3.550	0.636	1.889
	High school	0.323	1.382	0.081	1.084
	More than high school	0	0	0	0
Work Position	Foreperson	0.313	1.367	0.774 *	2.168 *
	Craftsperson/journeyperson	0.348	1.417	0.811 *	2.251 *
	Apprentice/Helper	0	0	0	0

The reference category: Continuous Training and Education at a score of 10; * Statistically significant at a 95% confidence interval, $p < 0.05$.

As the years of experience variable increases by one unit, the probability of the Tier II score being 0 or 5 increases by a factor of 1.089 or 1.054, respectively, when compared against a Tier II score of 10. Additionally, the likelihood of participants who work as forepersons or craftspersons/journeypersons scoring a 5 (100 h of training and skill updating within the last three years), rather than a 10 (more than 200 h of training and skill updating within the previous three years), are 2.168 or 2.251 times, respectively, when compared with apprentices/helpers. Individuals working as forepersons or craftspersons/journeypersons are more likely to have lower competency levels than apprentices/helpers.

The MLR analysis was also conducted for the project craft management elements, as follows: administrative, computer, planning, job management, and work record. Each dependent variable was evaluated separately to avoid the potential confounding effect of including multiple dependent variables in a single regression analysis.

As shown in Table 9, the chi-square values for administrative, computer, planning, job management, and work record elements were highly significant, with 16 degrees of freedom. The values of Nagelkerke R^2 were found to be 22%, 22%, 20%, 23%, and 50%, respectively, thus indicating that the explanatory variables in the MLR model were acceptable fits.

Table 9. Significance and fit of the MLR model for project craft management skills.

Project craft Management Element	Chi-Square Statics	Degree of Freedom	Significance Level
Administrative	116.76	16	0.001
Computer	25.24	16	0.001
Planning	42.25	16	0.001
Job management	42.19	16	0.001
Work record	298.50	16	0.001

As shown in Table 10, the results of the MLR for the "administrative skills" dependent variable indicate that five out of the six independent variables were found to be statistically significant. For every unit added to the number of certified trades, the likelihood of a Tier II score of 0 (no certification in administrative skills), rather than a 10 (certified in at least three trades), decreases by a factor of 0.384. The negative value of β (-0.068), regarding years of experience, indicates that any increase in the years of experience significantly decreases the likelihood of the Tier II score being 0. For the categorical independent variable, the likelihood of participants who have an educational level below a high school education attaining a 0 rather than a 10 is 7.826 times more likely than for those who pursued higher education. This result means that an individual who did not graduate high school is more likely to have a lower competency level than someone who has more than a high school education. Moreover, the likelihood of participants working as forepersons scoring a 0 rather than a 10 are 0.172 times greater than apprentices/helpers. In other words, individuals working as forepersons are less likely to have lower competency levels when compared with apprentices/helpers. These results suggest that the number of certified trades, years of experience, level of education, and work position are significant factors affecting the administrative skills of craft workers.

Table 10. Parameter estimates of the MLR for administrative skills.

Administrative		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Log of odds Ratio, β**	**Odds Ratio, Exp(β)**
Intercept		1.362 *		0.428	
Age		0.14	1.014	0.005	1.005
Number of certified trades		−0.384 *	0.681 *	−0.110	0.896
Years of experience		−0.068 *	0.935 *	−0.014	0.986
Craft training experience	-NO	0.839	2.313	0.352	1.421
	-YES	0	0	0	0
Education level	Less than high school	2.057 *	7.826 *	1.162	3.197
	High school	0.427	1.533	0.234	0.745
	More than high school	0	0	0	0
Work Position	Foreperson	−1.758 *	0.172 *	0.182	0.505
	Craftsperson/journeyperson	0.983	1.979	0.345	0.663
	Apprentice/helper	0	0	0	0

The reference category: Administrative at a score of 10; * Statistically significant at a 95% confidence interval, $p < 0.05$.

After conducting the MLR on the "computer skills" dependent variable, none of the six independent variables were statistically significant as shown in Table 11, thus they cannot explain the variations in the dependent variable.

Table 11. Parameter estimates of the MLR for computer skills.

Computer		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**
Intercept		−1.618 *		0.091	0
Age		0.013	1.013	0.023	1.023
Number of certified trades		−0.142	0.868	−0.114	0.893
Years of experience		−0.008	0.992	−0.037	0.963
Craft training experience	-NO	−0.022	0.978	0.490	1.632
	-YES	0	0	0	0
Education level:	Less than high school	1.252	3.498	−0.407	0.666
	High school	1.030	2.802	−0.268	1.308
	More than high school	0	0	0	0
Work Position	Foreperson	−1.580	0.206	−0.093	0.912
	Craftsperson/journeyperson	0.233	1.263	0.171	1.187
Apprentice/helper		0	0	0	0

The reference category: Computer at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

The MLR results in Table 12 for the "planning skills" dependent variable show that the number of certified trades, years of experience, and work position were significant independent variables with $p < 0.05$. For an increase of one unit in the number of certified trades, the likelihood of a Tier II score of 0 (no training or certifications in planning skills), rather than a 10 (certified in planning skills), decreases by a factor of 0.617. Similarly, as the years of experience increases by one unit, the likelihood of a Tier II score of 0, rather than a 10, decreases by a factor of 0.111. The likelihood of participants working as craftspersons/journeypersons scoring a 0 instead of a 10 is 3.638 times more likely than if an individual is an apprentice/helper. In other words, individuals working as craftspersons/journeypersons are more likely to have lower competency levels compared with apprentices/helpers with regard to planning skills.

Table 12. Parameter estimates of the MLR for planning skills.

Planning		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**
Intercept				−1.175	
Age			1.002	0.023	1.023
Number of certified trades			0.540 *	−0.208	0.812
Years of experience			0.895 *	−0.045	0.956
Craft training experience	-NO	0.444	1.559	0.254	1.289
	-YES		0	0	0
Education level:	Less than high school	2.023	7.564	1.676	5.342
	High school		1.272	0.658	1.932
	More than high school		0	0	0
Work Position	Foreperson	0.998	2.714	1.062	2.891
	Craftsperson/journeyperson		3.638 *	0.947	2.578
	Apprentice/helper		0	0	0

The reference category: Planning skills at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

One independent variable out of six was found to be a statistically significant factor for the "job management" dependent variable. For every unit added to the years of experience, the likelihood of a Tier II score of 0 (not certified in any job management skill), rather than a 10 (certified in job management functions), decreased by a factor of 0.197. The results in Table 13 suggest that years of experience and position significantly affect the job management skills of craft workers.

Table 13. Parameter estimates of the MLR for job management skills.

Job Management		Tier II at 0		Tier II Score at 5	
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**
Intercept		0.687		−0.521	
Age		0.020	1.020	0.002	1.002
Number of certified trades		−0.246	0.782	0.123	1.131
Years of experience		−0.197 *	0.821 *	−0.026	0.974
Craft training experience	-NO	0.770	2.159	0.789	2.200
	-YES	0	0	0	0
Education level	Less than high school	0.710	2.034	0.664	1.943
	High school	−0.072	0.931	0.503	1.653
	More than high school	0	0	0	0
Work Position	Foreperson	−0.292	0.747	−0.156	0.856
	Craftsperson/journeyperson	0.481	1.618	0.001	1.001
	Apprentice/helper	0	0	0	0

The reference category: Job management at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

For the last dependent variable, "work record," years of experience and education level were found to be statistically significant independent variables as shown in Table 14. As the years of experience increased by one unit, the likelihood of a Tier II score of 0 (weak work record), rather than a 10 (superior work record), decreases by a factor of 0.617. Regarding education level, the likelihood that participants who do not have a high school education will score a 0 rather than a 10 is 1.908 times more likely than those who completed their higher education. In other words, an individual without a high school diploma is more likely to experience a lower competency level in terms of work record when compared with those who have more than a high school education.

Table 14. Parameter estimates of the MLR for work record.

Work Record		Tier II Score of 0		Tier II Score of 5	
		Log of Odds Ratio, β	Odds Ratio, Exp(β)	Log of Odds Ratio, β	Odds Ratio, Exp(β)
Intercept		2.785 *		−1.804	
Age		0.005	1.005	0.14	1.015
Number of certified trades		−0.067	0.935	0.206	1.229
Years of experience		−0.055 *	0.947 *	−0.056	0.946
Craft training experience	-NO	1.147	3.150	0.150	1.162
	-YES	0	0	0	0
Education level	Less than high school	0.646 *	1.908 *	0.243	1.274
	High school	0.581	1.788	0.373	1.452
	More than high school	0	0	0	0
Work Position	Foreperson	−5.032	0.007	0.334	1.396
	Craftsperson/journeyperson	−0.584	0.558	0.978	2.658
	Apprentice/helper	0	0	0	0

The reference category: Work Record at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

5. Discussion

As discussed in the introduction, the Tier II workforce strategy can be used as a labor strategy to evaluate competency levels by measuring the presence of specific skills in the construction industry. Competency levels and skill gaps were identified for both single-skilled and multiskilled workers. Overall, multiskilled craft professionals have higher competency levels in most technical and management skills compared with single-skilled craft professionals. However, single-skilled and multiskilled workers had modest scores in terms of the work record elements, wherein participants were asked to evaluate their work performance in safety, quality, attendance, productivity, and initiative. This indicates room for improvement in this area for both groups. However, this element is not considered an individual skill. Single-skilled workers scored higher in the planning element than multiskilled craft workers.

The study found that the benefit of the multiskilling strategy, in terms of an individual's competency level, may become less significant once craft professionals become certified in more than two trades. This finding is consistent with previous research on multiskilling strategies [66]. When individuals are certified in more than two trades, their scores in technical and management skills tend to decrease. The study also revealed that the carpentry craft exhibits a greater level of competency when compared with the general workforce. This could be attributed to the fact that carpentry is a highly skilled trade that requires specialized education or several years of training [83].

To better understand the observed difference between Tier II single-skilled and multiskilled craft professionals, MLR was applied to each particular element of the technical and management Tier II skills, and it yielded the following findings, which can improve the competency level of each skill:

- Craft certification skills: Receiving training and being a craftsperson/journeyperson are positively associated with higher trade certifications. Additionally, young crasftpersons were less likely to be certified in multiple trades.
- Technical experience skills: Older, multiskilled craftspersons are likely to have more technical experience and higher competency levels.
- Continuous training and education skills: An experienced, multiskilled craft professional is likely to spend more time pursuing training and education while working as a foreperson, and a craftsperson/journeyperson spends less time in training and education, as compared with an apprentice/helper.
- Administrative skills: Those certified in multiple trades, having more work experience, and working as forepersons are positively associated with being certified in more administrative skills. Novice workers with a lower educational level usually have fewer administrative skills.
- Planning skills: Experienced craftspersons certified in more trades are more likely to have high competency planning skills. Additionally, those working as craftsper-

sons/journeypersons have a higher probability of not being certified in any planning skills as compared with individuals working as apprentices/helpers.

- Job management: Experienced craftspersons tend to be more competent in terms of job management than novice craftspersons.
- Work record: Although single-skilled and multiskilled craftspersons scored low in terms of work record, experienced individuals with higher education levels tend to exhibit higher work record competency levels.

One limitation of the RT-370 craft survey is that the carpentry craft represents the most common trade as the carpenters' union helped distribute the survey. Another limitation is that most participants were concentrated primarily around east urban areas of the United States. Regardless, the RT-370 data remained useful for this research. Moreover, the survey results are based on whether the participants self-identified as multiskilled. This was not verified by the research through assessment methods.

To guide future research, it would be beneficial to replicate the study across different construction trades to assess the consistency of the Tier II competency level results. Moreover, an investigation of the desired competency level for each skill is necessary.

6. Conclusions

This research investigated the influence of the multiskilling strategy on the competency levels of the construction industry workforce. More specifically, the study employed a workforce strategy, referred to as Tier II strategy metrics, to assess and describe the current competencies of the multiskilled and single-skilled workforce in craft technical and management skills. These skills, including craft certification, technical experience, continuous training and education, administration, computer skills, planning, job management, and work record, were identified by Tier II as being essentially individual skills. The results show substantial evidence that multiskilled workers have greater competency levels compared with single-skilled workers in all project craft technical and management skills except the planning element.

Furthermore, an MLR model was developed to predict which independent variables lead to higher competency levels. Of the six independent variables, the number of certified trades and years of experience were the most critical variable in predicting high competency for both the project craft technical and management Tier II scores. On the other hand, age, training, education level, and work position do not appear to influence the majority of the project craft technical and management skills.

The implementation of multiskilling can be effective and efficient to maximize the benefit of the Tier II strategy in the construction industry, focusing on utilizing fewer, more qualified, and more highly educated competent workers.

The findings of this research have significant theoretical and practical implications. First, the study made an important theoretical contribution by emphasizing the significance of adopting the multiskilling strategy for enhancing individuals' competency levels. Second, the comprehensive competency assessment can be used by training providers to develop appropriate training plans for implementing both the multiskilling strategy and Tier II strategy. Moreover, once the competency levels have been identified, policy makers, companies, and trainers will have a better understanding of how to create an efficient training policy tailored to each category of workers. Finally, the MLR is used to define and study the most effective factor among six explanatory variables for both project craft technical skills and project craft management skills. The results obtained from this model can be used to provide insights into the extent to which these factors impact each skill. Therefore, the current study makes significant theoretical and practical contributions, which can significantly improve workforce management practices.

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Appendix A

Table A1. *t*-test analysis for Figure 4: Tier II element scores based on the overall multiskilled craft professionals vs. overall single-skilled craft professionals.

Element	Workforce	Sample	Mean	Median	Std. Deviation	*p*-Value
Craft Certification	Single-skilled Multiskilled	979 716	2.63 7.58	3.0 10.0	0.9 2.5	0.000
Technical Experience	Single-skilled Multiskilled	470 305	5.78 7.02	5.0 10.0	4.23 3.60	0.002
Continuous Training and Education	Single-skilled Multiskilled	893 652	5.55 6.30	5.0 5.0	3.61 3.24	0.000
Administrative	Single-skilled Multiskilled	850 629	4.65 5.45	5.0 5.0	4.10 3.98	0.000
Computer	Single-skilled Multiskilled	362 495	6.26 6.86	5.0 5.0	3.36 3.24	0.009
Planning	Single-skilled Multiskilled	303 337	6.82 5.61	5.0 5.0	3.48 3.86	0.000
Job Management	Single-skilled Multiskilled	340 310	6.36 7.02	5.0 10.0	3.76 3.42	0.020
Work Record	Single-skilled Multiskilled	979 716	3.94 4.32	0.0 5.0	4.45 4.42	0.082

Table A2. *t*-test analysis for Figure 5: Tier II score based on an individual's primary craft (carpentry).

Element	Workforce	Sample	Mean	Median	Std. Deviation	*p*-Value
Craft Certification	Single-skilled Multiskilled	79 492	2.59 7.96	3.0 10.0	1.04 2.50	0.000
Technical Experience	Single-skilled Multiskilled	304 198	6.22 8.89	5.0 10.0	4.47 2.89	0.000
Continuous Training and Education	Single-skilled Multiskilled	647 458	6.89 7.41	10.0 10.0	3.79 2.90	0.010
Administrative	Single-skilled Multiskilled	613 442	6.62 7.41	10.0 10.0	3.92 2.90	0.000
Computer	Single-skilled Multiskilled	464 348	7.70 7.59	10.0 10.0	2.79 2.90	0.585
Planning	Single-skilled Multiskilled	250 219	5.54 7.59	5.0 10.0	4.05 2.90	0.000
Job Management	Single-skilled Multiskilled	259 229	6.62 7.78	5.0 10.0	3.74 2.90	0.000
Work Record	Single-skilled Multiskilled	704 492	5.14 6.11	5.0 10.0	4.49 4.46	0.000

Table A3. Full MLR result for Table 6: Parameter estimates of the MLR for craft certification skills.

Craft Certification		Tier II Score of 0: Log of Odds Ratio, β	Tier II Score of 0: Odds Ratio, Exp(β)	Tier II Score of 0: Wald Test	Tier II Score of 0: Sig.	Tier II Score of 5: Log of Odds Ratio, β	Tier II Score of 5: Odds Ratio, Exp(β)	Tier II Score of 5: Wald Test	Tier II Score of 5: Sig.
Intercept		1.727 *		4.870	0.027	0.616		0.692	0.405
Age		−0.015	0.985	0.843	0.359	0.001	1.001	0.086	0.770
Years of experience		−0.229 *	0.795 *	13.788	0.000	−0.035	0.965	1.192	0.275
Craft training experience	-NO	1.457 *	4.292 *	5.560	0.018	-0.243	0.784	0.038	0.845
	-YES	0							
Education level	Less than high school	−0.43	0.958	0.141	0.708	−0.727	0.483	0.805	0.370
	High school	0.227	1.255	0.248	0.619	0.046	1.047	0.003	0.958
	More than high school	0							
Work Position	Foreperson	−0.664	0.515	0.627	0.429	−0.061	0.941	0.001	0.981
	Craftsperson/journeyperson	−2.255 *	0.105 *	14.770	0.001	−0.277	0.758	0.884	0.347
	Apprentice/helper	0							

The reference category: Craft Certification at a score of 10; * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A4. Full MLR result for Table 7: Parameter estimates of the MLR for technical experience skills.

Technical Experience		Tier II Score of 0: Log of Odds Ratio, β	Tier II Score of 0: Odds Ratio, Exp(β)	Tier II Score of 0: Wald Test	Tier II Score of 0: Sig.	Tier II Score of 5: Log of Odds Ratio, β	Tier II Score of 5: Odds Ratio, Exp(β)	Tier II Score of 5: Wald Test	Tier II Score of 5: Sig.
Intercept		6.769 *		74.595	0.000	5.331 *		63.534	0.000
Age		−0.104 *	0.901 *	36.865	0.000	−0.088 *	0.961 *	41.94	0.000
Number of certified trades		−0.324 *	0.724 *	7.738	0.004	−0.036	0.964	0.176	0.675
Craft training experience	-NO	0.392	1.480	0.048	0.827	−0.206	0.813	0.128	0.721
	-YES	0							
Education level	Less than high school	−0.688	0.502	0.028	0.868	−1.189	0.305	1.955	0.162
	High school	−0.431	0.650	2.262	0.133	−0.073	0.929	0.181	0.671
	More than high school	0							
Work Position	Foreperson	−5.054 *	0.006 *	70.477	0.000	−3.003 *	0.050 *	53.541	0.000
	Craftsperson/journeyperson	−3.692 *	0.025 *	74.853	0.000	−2.182 *	0.113 *	30.316	0.000
	Apprentice/helper	0							

The reference category: Technical Experience at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A5. Full MLR result for Table 8: Parameter estimates of the MLR for continuous training and education skills.

Continuous Training and Education		Tier II Score of 0: Log of Odds Ratio, β	Tier II Score of 0: Odds Ratio, Exp(β)	Tier II Score of 0: Wald Test	Tier II Score of 0: Sig.	Tier II Score of 5: Log of Odds Ratio, β	Tier II Score of 5: Odds Ratio, Exp(β)	Tier II Score of 5: Wald Test	Tier II Score of 5: Sig.
Intercept		−2.414 *		11.102	0.000	−1.883 *		21.106	0.001
Age		0.016	1.017	0.292	0.589	0.022	1.022	4.213	0.052
Number of certified trades		−0.678 *	0.508 *	13.969	0.000	−0.126	0.881	1.856	0.173
Years of experience		0.086 *	1.089 *	80.510	0.004	0.053 *	1.054 *	8.312	0.004
Craft training experience	-NO	−1.595	0.203	0.847	0.357	−0.292	0.746	0.000	0.987
	-YES	0							
Education level	Less than high school	1.267	3.550	2.933	0.087	0.636	1.889	0.271	0.603
	High school	0.323	1.382	1.455	0.228	0.081	1.084	0.068	0.794
	More than high school	0	0			0	0		
Work Position	Foreperson	0.313	1.367	0956	0.328	0.774 *	2.168 *	5.380	0.020
	Craftsperson/journeyperson	0.348	1.417	1.035	0.309	0.811 *	2.251 *	9.139	0.003
	Apprentice/Helper	0							

The reference category: Continuous Training and Education at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A6. Full MLR result for Table 10: Parameter estimates of the MLR for administrative skills.

Administrative		**Tier II Score of 0**				**Tier II Score of 5**			
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**
Intercept		1.362 *		4.413	0.036	0.428		0.011	0.918
Age		0.14	1.014	1.347	0.246	0.005	1.005	1.003	0.317
Number of certified trades		−0.384 *	0.681 *	14.902	0.000	−0.110	0.896	0.881	0.348
Years of experience		−0.068 *	0.935 *	5.506	0.19	−0.014	0.986	0.074	0.785
Craft training experience	-NO	0.839	2.313	1.251	0.263	0.352	1.421	1.257	0.262
	-YES	0							
Education level	Less than high school	2.057 *	1.154	3.181	0.047	1.162	1.103	1.111	0.292
	High school	0.427	1.533	1.348	0.246	0.234	0.745	0.014	0.906
	More than high school	0							
Work Position	Foreperson	−1.758 *	0.172 *	16.673	0.000	0.182	0.505	0.071	0.790
	Craftsperson/journeyperson	0.983	1.979	2.516	0.113	0.345	0.663	0.308	0.579
	Apprentice/helper	0							

The reference category: Administrative at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A7. Full MLR result for Table 11: Parameter estimates of the MLR for computer skills.

Computer		**Tier II Score of 0**				**Tier II Score of 5**			
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**
Intercept		−1.618 *		3.752	0.043	0.091	0	0.054	0.817
Age		0.013	1.013	0.420	0.517	0.023	1.023	2.550	0.110
Number of certified trades		−0.142	0.868	0.977	0.323	−0.114	0.893	1.069	0.301
Years of experience		−0.008	0.992	1.43	0.706	−0.037	0.963	3.455	0.063
Craft training experience	-NO	−0.022	0.978	0.597	0.440	0.490	1.632	0.043	0.837
	-YES								
Education level:	Less than high school	1.252	3.498	1.027	0.311	−0.407	0.666	1.311	0.252
	High school	1.030	2.802	7.345	0.070	−0.268	1.308	1.254	0.263
	More than high school	0	0			0	0		
Work Position	Foreperson	−1.580	0.206	6.571	0.050	−0.093	0.912	0.852	0.356
	Craftsperson/journeyperson	0.233	1.263	0.137	0.712	0.171	1.187	0.170	0.680
	Apprentice/helper	0							

The reference category: Computer at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A8. Full MLR result for Table 12: Parameter estimates of the MLR for planning skills.

Planning		**Tier II Score of 0**				**Tier II Score of 5**			
		Log of Odds Ratio, β	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**	**Log of Odds Ratio, β**	**Odds Ratio, Exp(β)**	**Wald Test**	**Sig.**
Intercept		0.582		0.087	0.769	−1.175		3.621	0.057
Age		0.002	1.002	0.249	0.618	0.023	1.023	2.328	0.127
Number of certified trades		−0.617 *	0.540 *	11.436	0.000	−0.208	0.812	3.703	0.054
Years of experience		−0.111 *	0.895 *	5.295	0.021	−0.045	0.956	0.905	0.341
Craft training experience	-NO	0.444	1.559	0.000	0.998	0.254	1.289		
	-YES	0							
Education level	Less than high school	2.023	7.564	0.269	0.604	1.676	5.342	1.169	0.280
	High school	0.241	1.272	0.286	0.593	0.658	1.932	3.823	0.051
	More than high school	0	0			0	0		
Work Position	Foreperson	0.998	2.714	0.436	0.509	1.062	2.891	2.234	0.135
	Craftsperson/journeyperson	1.291 *	3.638 *	4.063	0.044	0.947	2.578	2.571	0.109
	Apprentice/helper	0							

The reference category: Planning skills at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A9. Full MLR result for Table 13: Parameter estimates of the MLR for job management skills.

Job Management		Tier II at 0: Log of Odds Ratio, β	Odds Ratio, Exp(β)	Wald Test	Sig.	Tier II score at 5: Log of Odds Ratio, β	Odds Ratio, Exp(β)	Wald Test	Sig.
Intercept		0.687		0.311	0.577	−0.521		0.248	0.619
Age		0.020	1.020	0.756	0.384	0.002	1.002	0.035	0.851
Number of certified trades		−0.246	0.782	1.866	0.172	0.123	1.131	0.591	0.442
Years of experience		−0.197 *	0.821 *	17.082	0.000	−0.026	0.974	0.194	0.659
Craft training experience	-NO	0.770	2.159	278.390	0.000	0.789	2.200		
	-YES	0							
Education level	Less than high school	0.710	2.034	0.000	0.998	0.664	1.943	0.394	0.530
	High school	−0.072	0.931	0.037	0.874	0.503	1.653	1.223	0.296
	More than high school	0							
Work Position	Foreperson	−0.292	0.747	0.120	0.729	−0.156	0.856	0.000	0.999
	Craftsperson/journeyperson	0.481	1.618	0.725	0.395	0.001	1.001	0.030	0.863
	Apprentice/helper	0							

The reference category: Job management at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

Table A10. Full MLR result for Table 14: Parameter estimates of the MLR for job work record.

Work Record		Tier II Score of 0: Log of Odds Ratio, β	Odds Ratio, Exp(β)	Wald Test	Sig.	Tier II Score of 5: Log of Odds Ratio, β	Odds Ratio, Exp(β)	Wald Test	Sig.
Intercept		2.785 *		19.355	0.000	−1.804		2.572	0.109
Age		0.005	1.005	0.001	0.984	0.14	1.015	0.218	0.641
Number of certified trades		−0.067	0.935	0.12	0.912	0.206	1.229	3.695	0.055
Years of experience		−0.055 *	0.947 *	4.168	0.041	−0.056	0.946	3.035	0.082
Craft training experience	-NO	1.147	3.150	0.882	0.348	0.150	1.162		
	-YES	0							
Education level	Less than high school	0.646 *	1.908 *	1.245	0.265	0.243	1.274	0.091	0.763
	High school	0.581	1.788	3.823	0.051	0.373	1.452	0.561	0.454
	More than high school	0	0			0	0		
Work Position	Foreperson	−5.032	0.007	80.139	0.052	0.334	1.396	0.247	0.619
	Craftsperson/journeyperson	−0.584	0.558	1.742	0.187	0.978	2.658	1.587	0.208
	Apprentice/helper	0							

The reference category: Work Record at a score of 10, * Statistically significant at a 95% confidence interval, $p < 0.05$.

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