



Assessing Automotive Graduates' Readiness and Skills Gaps for Electric Vehicle Repair and Maintenance: Evidence from Automotive Service Garages in Kumasi, Ghana

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Abstract: Ghana's automotive sector has significant opportunities for the transition from Internal Combustion (IC) to electric vehicles. Current training remains largely IC-engine focused. TVET programmes, apprenticeship training, and automotive education curricula must align with emerging EV technologies and evolving workforce needs. This study aimed to assess automotive graduates' preparedness for electric vehicle (EV) repair and maintenance in Kumasi, Ghana, identify critical competency gaps, and determine priorities for strengthening workforce readiness. A cross-sectional survey was conducted among automotive engineering graduates, technicians, industry professionals, and academic staff in Kumasi, Ghana, using a multi-stage stratified sampling approach. A total of 753 eligible respondents provided usable responses to the structured online questionnaire. Data were analysed using descriptive and inferential statistical techniques, and all statistical analyses were performed in R version 4.3.2 and IBM SPSS Statistics version 20. The study revealed a substantial competency gap in EV knowledge, technical skills, and practical competencies, with 51.1% of respondents lacking knowledge in EV fault diagnosis. The findings underscore the need to prioritize periodic practical EV repair and maintenance training, industry internships and apprenticeships, and stronger collaboration between industry and training institutions to enhance graduate competencies and workforce readiness for the transition to electric mobility in Ghana.

Keywords: Electric Vehicle (EV), Skills gap, Workforce readiness, Graduates' Readiness, Automotive, Propensity Score Matching (PSM)

INTRODUCTION

This paper aimed to conduct a comprehensive assessment of Ghana's automotive graduates' skills readiness for electric vehicle repair and maintenance and the evidence of competency gaps within the automotive service garages using the Ashanti region as a case study. The comprehensive survey was designed to address five interrelated research questions concerning the readiness of Ghana's automotive workforce for the transition to electric mobility. Specifically, the study sought to determine (i) what knowledge, technical skills, and practical competencies are required by automotive service garages in Ghana, particularly those in the Ashanti Region, to safely and effectively diagnose, repair, and maintain emerging electric vehicle (EV) technologies [1, 2]; (ii) to what extent automotive graduates possess the requisite knowledge, technical skills, and practical competencies for

EV repair and maintenance, including competencies in high-voltage electrical systems and safety, traction batteries and battery management systems, electric motors and motor control, power electronics and inverters, charging systems, vehicle diagnostics, thermal management, regenerative braking, and associated electronic and communication systems [1, 2, 3]; (iii) the extent and nature of the competency gaps between the skills required by automotive service garages and those possessed by automotive graduates, thereby providing empirical evidence of the preparedness of the emerging automotive workforce for EV servicing [1, 3, 4]; (iv) the educational, institutional, and industry-related factors contributing to identified competency gaps, including the relevance of existing curricula, adequacy of practical and hands-on training, instructor expertise, availability and accessibility of EV-specific training equipment and facilities, opportunities for industry exposure and workplace learning, and access to emerging automotive technologies [1, 4]; and (v) what curriculum reforms, industry-training institution partnerships, professional development initiatives, practical training strategies, equipment and infrastructure investments, and policy interventions should be prioritized by automotive training institutions, industry stakeholders, and policymakers to strengthen the EV repair and maintenance competencies of automotive graduates and enhance Ghana's readiness for the broader transition toward electric mobility in the African transportation system [1, 2, 3, 4]. Unlike other skills gap assessments that focus either on employability or soft skills in higher education, this paper identifies a mismatch between graduate competencies and industry requirements and emphasizes the need for the automotive service industry and workforce transition toward electric vehicle repair and maintenance in Ghana rather than education alone. It further recommends proven curriculum reforms, industry-training institution partnerships, professional development initiatives, practical training strategies, equipment and infrastructure investments, and policy interventions that have been adopted in other developed and developing countries around the globe to improve the adoption of EV technologies, technical competency, and readiness of Automotive graduates and transportation systems.

As the global automotive industry undergoes a profound shift from Internal Combustion (IC) engine vehicles to Electric vehicles, this creates significant opportunities for the automotive sector in Sub-Saharan Africa [5, 6, 7]. There is therefore a need for automotive graduates to be ready for the emerging market. To achieve this goal, skills development at Technical Universities and Technical and Vocational Education and Training (TVET), and apprenticeships in the automotive industry must be employable, and the curriculum must also align with emerging trends in electric vehicles and workforce development [2, 3, 8, 9]. Automotive graduates and technicians who operate in both formalized garages and the informal sector have limited exposure to modern technologies and knowledge on electric vehicles (EVs), hybrid systems, and digital diagnostics [3, 4, 9]. In Ghana and other sub-Saharan countries, technical education for automotive institutions predominantly focuses on traditional internal combustion engine (ICE) repair, failing to align with evolving industry demands [10]. Despite Ghana's industrial policy focus on automotive growth, a substantial skills gap persists. According to [11], most youth in the automotive sector are trained informally and lack the competencies needed to service emerging technologies such as EVs and digital diagnostics. Repairs and maintenance in the automotive sector are predominantly carried out by informal/roadside mechanics and artisanal manufacturing clusters in the municipality of Suame in Kumasi, one of the largest clusters of automotive engineering and artisanal manufacturing in West Africa [12, 13, 14]. In the

past few decades, these workshops have gained extensive knowledge of the maintenance and repair of conventional/IC vehicles. However, the shift toward EVs introduces new challenges in terms of emerging technologies and technical know-how, which could surpass the expertise of the informal/roadside mechanics and local artisans who are used to repairing conventional vehicles with IC engines [15, 16]. There is therefore some gap in the readiness of automotive technicians to diagnose high-voltage electrical systems, work with battery technology, meet EV safety specifications, and use digital diagnostic tools with modern electric vehicles [17, 18, 19]. Existing TVET curricula are outdated, training equipment is inadequate, and there is a mismatch between industry needs and graduate competencies [19, 20]. Consequently, labour market entrants are ill-prepared for modern automotive roles, leading to underemployment and limited entrepreneurship among youth [18, 20]. These systemic inefficiencies are further exacerbated in the Ashanti region, where Suame Magazine is located and where youth unemployment remains disproportionately high and access to inclusive training opportunities is constrained [21, 22, 23].

MATERIALS AND METHODS

Research Design

This study was directed to the automotive sector in Kumasi made up of automotive engineering graduates, automotive engineering technicians, and automotive engineering professionals. The study focussed specifically on the automotive engineering graduates from Ghanaian universities and technical institutions trained from 2018 - 2024. Other population included the technicians working in the automotive repair workshops, vehicle dealerships, service centres and lecturers and instructors working in the automotive engineering departments. The sampling frame also included industry personnel such as service advisors, supervisors, managers and other staff who participated in automotive-related activities. The groups were chosen due to their knowledge, practical experiences, and professional context on the current status of electric vehicle (EV) skills, identification of existing competency gaps, and recommendations for strengthening EV workforce preparedness in Kumasi.

Study Population and Sampling

Target Population and Sampling Frame

The target population for this study comprised automotive engineering graduates, technicians, and professionals working within the automotive sector in Kumasi. Specifically, the study targeted graduates of automotive engineering programmes from Ghanaian universities and technical institutions who completed their studies between 2018 and 2024. In addition, the population included technicians employed in automotive repair workshops, vehicle dealerships, and service centres, as well as lecturers and instructors teaching in automotive engineering departments. The sampling frame also encompassed industry professionals, including service advisors, supervisors, managers, and other personnel engaged in automotive-related operations. These groups were selected because they possess the knowledge, practical experience, and professional insights required to assess the current state of electric vehicle (EV) skills, identify existing competency gaps, and propose appropriate strategies for strengthening EV workforce preparedness in Kumasi.

Inclusion Criteria:

1. Current employment or recent graduation (within 5 years) in the automotive sector
2. Age 18 years or older
3. Willingness to provide informed consent and complete the survey
4. Able to understand and respond to survey questions in English
5. Minimum of 6 months of experience in the automotive sector (for professionals)

Exclusion Criteria:

1. Individuals not directly involved in automotive repair, maintenance, or engineering
2. Professionals with less than 6 months of automotive sector experience
3. Individuals unable or unwilling to provide informed consent
4. Incomplete survey responses (excluded during data cleaning)

Sampling Technique and Proportional Allocation

The sampling method used was multi-stage stratified sampling to ensure that the various classes of respondents that are involved in the automotive sector in Kumasi were adequately represented. This was deemed suitable due to the different professional groups and skill sets in the target audience in terms of EV technologies. Before sampling, the study took into account the stratification of the population which helps to reduce sampling bias and increase the representativeness of the respondents selected for the study. The first stage involved stratification of the target population according to the designation of the respondents in the four major professional groups. The automobiles engineering graduates represented the largest group of the sample (35%), followed by technicians and technical staff (25%), industry people (managers, supervisors, service advisors) (25%) and academic staff (lecturers, instructors in automotive engineering departments) (15%). The proportions were established in the light of the estimated distribution of automotive professionals in Kumasi, which was based on institutional records, Ghana Automotive Development Policy (2022), and enrolment statistics of the automotive engineering programmes in the technical and tertiary institutions in the city. In the second stage proportional allocation was used to allocate the respondents across the four strata on the basis of their predetermined proportions with a total sample size of 750. As a result, there were 263 respondents in the graduate category, 188 in technician and technical staff, 188 industry professionals, and 111 academic staff. This proportional allocation allowed each professional group to be included in the sample proportionate to the size of the target population, which enhanced the precision and generalizability of the results of this study. Simple random sampling was done within each stratum to select eligible participants in the final stage. Sampling was done based on the sampling frames available, such as alumni databases, institutional registers and membership lists of professional associations as available. Simple random sampling method was used to ensure that each eligible person in each stratum had equal probability of being selected, which minimized selection bias, increased reliability and validity of study results.

Sample Size Justification

The target sample size of 750 was determined using the Cochran formula for sample size calculation:

$$n_0 = \frac{Z^2 \times p \times (1 - p)}{e^2}$$

Where:

- $Z = 1.96$ (95% confidence level)
- $p = 0.5$ (maximum variability, conservative estimate)
- $e = 0.05$ (margin of error)

$$n_0 = \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2} = 384.16$$

Accounting for an estimated 20% non-response rate:

$$n = \frac{384.16}{0.8} = 480.2$$

To ensure adequate power for subgroup analyses and multivariate modelling, the sample was increased to 750 respondents. The final analytical sample of 753 respondents (achieved response rate: 100.4% of target) provided sufficient statistical power for the planned analyses.

Response Rate and Sample Composition

Within the teaching institutions, automotive workshops, automotive dealerships, and automotive-related institutions of Kumasi, a total of 800 potential respondents were approached. Of these, 753 responded successfully, which is a 94.1% response rate. After data screening and cleaning, data from all 753 questionnaires that fulfilled the study's inclusion criteria and provided adequate data for statistical analysis were kept for final analysis. The final sample composition showed a close match with the desired sampling design with slight differences in the proportions of each category of professionals. The number of graduates in this survey, 270 (35.9%), slightly outpaced the target of 35.0% by 0.9 percentage points. The "Other" category was made up of various industry professionals, accounting for 297 respondents (39.4%) which is 14.4 percentage points over the planned proportion of 25.0%. Technicians responded 123 (16.3%) compared with the target of 25.0% which was 8.7 percentage points below. Likewise, academic staff including lecturers, supervisors and managers had 63 (8.4%) respondents, representing a deviation of 6.6 percentage points from the targeted 15.0%. It is recognized that there may be sampling imbalance due to the overrepresentation of industry people and underrepresentation of technicians and academic staff. Propensity score matching (PSM) was used as outlined in Section 3.6.2 to reduce the impact of this imbalance and ensure comparability of groups in the study. This strategy ensured that the selection process was unbiased, resulting in the equating of observed characteristics in the treatment and control groups, and increasing the internal validity of the study results.

Questionnaire Design and Development

The questionnaire for this study was designed in a systematic manner, based on a thorough literature review and existing competency frameworks in the field of electric vehicle (EV) technologies. The purpose of the literature review was to uncover validated instruments and key constructs in technical competency assessment of EVs, diagnostic skills assessment, occupational safety awareness, and readiness level of automotive engineering graduates in the changing automotive industry. The competency standards of the International Labour Organisation (ILO), National Occupational Standards (NOS) of Automotive Engineering from the United Kingdom, Australia, and South Africa, validated instruments from past studies on EV skills assessment, industry standards established by the Society of Automotive Engineers (SAE) and the International Electrotechnical Commission (IEC), the Ghana Automotive Development Policy (2022) skills gap assessment framework, and curriculum documents of automotive engineering courses from Ghanaian universities and technical institutions were among the major sources that were consulted during development. Based on the identified results from the literature review and the theoretical framework developed for the study, 85 initial items for the questionnaire were created that are representative of the key dimensions of EV workforce preparedness. The questionnaire was organized into four sections. The first section consisted of four questions related to personal information such as gender, age, educational level, and professional designation.

The second section had nine questions, primarily about the coverage of curriculum in EV, hands-on experience, institutional support, and teaching practices. The third section consisted of nine questions that assessed the industry's expectations of the critical technical skills, including EV fault diagnosis, the use of diagnostic tools, understanding of EV fault codes, and knowledge of large components in EVs. The last section included fifteen questions that asked the grads about their opinion on the academia-industry gap, on the theory-practice gap, on the amount of professional training that is received, on what are the barriers to developing competency in EV, and on what are the recommendations for making the grads more competent. The items in the questionnaire were created by mapping directly to the theoretical constructs of the research, and all the items were conceptually linked to the research objectives in order to improve the quality and relevance of the questionnaire. The preliminary questionnaire was then tested by automotive engineering educators and experts for clarity, relevance of content and suitability. Furthermore, focus groups were organised with experts from the automotive sector to capture the present needs in the workplace, new developments in EV and the skills that are expected from a graduate. The questionnaire was refined after receiving feedback from these consultations prior to its validity and reliability measures.

Data Collection Procedures

This study was carried out over a period of 12 weeks, from January to March 2026. The process was systematic to guarantee that the responses were of high quality and ethical, as well as effective participant recruitment and accurate data collection. Ethical clearance was obtained from the Institutional Review Board of the lead institution (Ref. No: IRID/EC2026/HS00162). Formal approval of the participating institutions, automotive workshops, dealerships, service centres and other relevant organisations that participated in the study was also gained. The respondents were drawn from the respondents who are

the graduate engineers, technicians, teachers and workers from the automotive sector in the study area. The recruitment process involved several methods such as sending emails via alumni networks and professional organizations, reaching out to automotive workshops and service centres directly, and using online job portals and platforms. Participants who were hard to access using traditional methods of recruitment were identified through referral and snowball sampling techniques. All participants gave informed consent electronically prior to completing the questionnaire. The consent process included detailed explanation of the purpose of the study, that participation was voluntary, that participants could withdraw at any time without penalty, that the data would be treated confidentially and anonymised, how the data would be stored and how participation might lead to risks or benefits. Those who did not agree to the consent terms were not allowed to proceed with the survey. Only an online survey platform (Google Forms) was used to gather data. Eligible individuals were targeted via e-mail, LinkedIn profile post, and appropriate communication channels with the electronic questionnaire link. The online format of the survey allowed data to be collected efficiently, avoided data entry errors and direct transfer of responses into a secure database. The questionnaire was filled in by the participants themselves, without the researchers being in direct contact with them, reducing the possibility of bias and motivating the participants to respond honestly. In order to deliver data quality several quality control measures were put in place during the data collection. Regular monitoring was carried out on rates of response and incomplete submissions were checked and rejected where required. Previously the data gathered were checked for missing values, inconsistencies, and logical errors. The electronic aspect of the Google Forms platform also enabled the automatic organisation of the data, the validation checks and the efficient preparation of the data for statistical analysis.

Data Pre-Processing and Variable Coding

In this step, the data are pre-processed and the variables are coded. The data in this step are pre-processed and variables coded. The collected data were systematically pre-processed to ensure data quality, consistency and appropriateness for the model, prior to statistical analysis. Data cleaning comprised examination of the dataset for missing values, inconsistencies in the answers given, and possible outlying cases. Data for cases with incomplete responses were treated by listwise deletion, which eliminated 18 cases (2.4% of total responses). Thus, a total of 753 respondents were included as the final analytical sample. The amount of missing data was relatively small (2.4%) and was assumed to be missing completely at random (MCAR), which allows listwise deletion to be used for statistical techniques used in the study. After data cleaning, all the study variables were coded and converted to numeric coding for statistical analysis and modelling. Yes = 1, No = 0 (binary variables). The five-point Likert scale was used to measure ordinal variables, with responses coded as Strongly Disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; and Strongly Agree = 5. Likewise, the competencies measured on a four-point scale were coded Beginner = 1, Intermediate = 2, Proficient = 3, and Expert = 4. The nominal data were also recorded numerically, e.g. professional designation, Graduate = 1, Technician = 2, Service Advisor = 3, Supervisor = 4, Manager = 5 and Lecturer = 6 respectively, and education = MVTI = 1, Diploma = 2, HND = 3, BEng/BTech = 4 and MEng/MTech = 5 respectively. Analytical variables were created for major outcome measures by combining variables. Overall EV repair

knowledge item scores were computed by adding the scores of 12 knowledge items, which had good internal consistency (Cronbach's $\alpha = 0.84$).

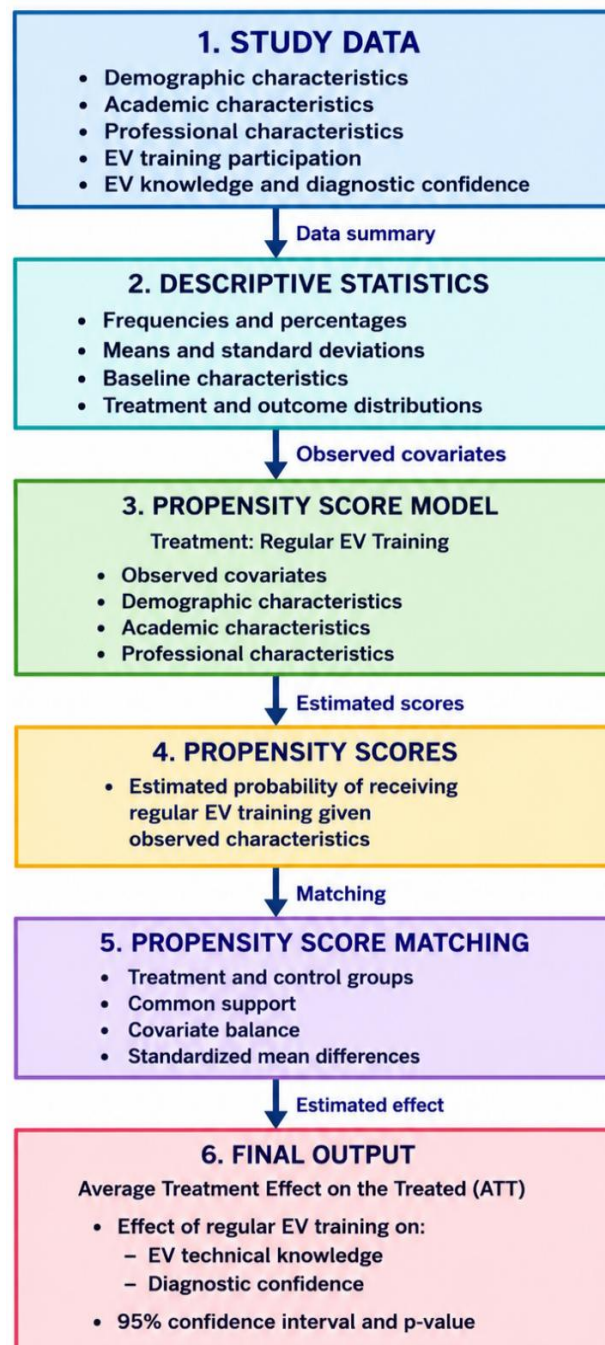


Figure 1: Sequential Analytical Pipeline for Propensity Score Matching Analysis of Regular EV Training Effects on EV Technical Knowledge and Diagnostic Confidence

The resulting scores ranged from 12 to 60; the higher the score the more the respondents knew about EV repair. To make for easy interpretation, the composite score was then converted to a four-point competency scale (Beginner (1), Advanced (2), Expert (3), High-Expert (4)). The same was true of an overall diagnostic confidence rating based on summing responses to eight items of the confidence rating scale, which also had high reliability (Cronbach's $\alpha = 0.87$). The confidence scores were between eight and 40, with

higher scores indicating more confidence in diagnosis of EV systems. The main treatment variable for the propensity score matching analysis was regular EV training participation. This was a binary question that was created from the question, "Have you had any formal or informal training in the last 12 months on EV-specific issues? The answer was dichotomized as Yes = 1 (if respondents had been trained in EV) and No = 0 (if respondents had not been trained in EV). This variable was used as the treatment indicator variable to estimate the effect of EV training on knowledge and diagnostic confidence variables. The study used mainly categorical variables and ordinal variables and thus analytical techniques suitable for these types of variables were used. When a relationship existed between the two variables, and a sufficient number of response categories and adequate distributional characteristics, ordinal variables were converted to continuous measures. This method allowed the use of the more suitable statistical techniques for measuring the variables involved, in addition to ensuring valid and reliable results for the study.

Data Analysis

Data were analysed using both descriptive and inferential statistics to summarize the characteristics of the respondents as well as to identify patterns in the development of electric vehicle (EV) competency and assess the impact of continuous EV training on the technical knowledge and diagnostic confidence of respondents. The analytical framework consisted of two major components: descriptive statistical analysis and propensity score matching (PSM). The distribution of demographic characteristics, EV-related knowledge, skills, exposure to training, and perceptions of workforce preparedness were summarized using descriptive analysis. To control for potential selection bias due to the differences in the training sample and the non-trained sample, propensity score matching was then performed to estimate the causal effect of regular EV training.

Descriptive Statistics

Descriptive statistics were calculated for all the study variables to get a general sense of the characteristics of respondents as well as the distribution of the key study variables. Frequencies and percentages, along with the corresponding 95% confidence intervals (CIs), were used to summarize categorical variables to represent the precision of estimated proportions. Measures of central tendency and variability were used for composite and continuous variables, such as EV knowledge and diagnostic confidence scores, as appropriate. The descriptive results helped to frame the respondents' demographic background, academic background, technical skills, work experience, and gaps in EV skills development.

Propensity Score Matching Analysis

Propensity Score Matching (PSM) was employed to estimate the causal effect of regular EV training on technical knowledge and diagnostic confidence while controlling for potential selection bias arising from non-random participation in EV training. Since individuals who participate in EV training may differ systematically from those who do not, PSM was used to create comparable treatment and control groups based on observed characteristics. The

propensity score represents the probability that an individual receives EV training given their observed characteristics.

The propensity scores were estimated using binary logistic regression, where regular EV training status was specified as the dependent variable and selected demographic, academic, and professional characteristics were included as predictors. The logistic regression model was expressed as:

$$P(T = 1 | X) = 1 / [1 + e^{-(B_0 + B_1X_1 + B_2X_2 + \dots + B_kX_k)}] \quad (1)$$

Where:

- $T = 1$ if the respondent received regular EV training and $T = 0$ if the respondent did not receive training.
- X represents the vector of observed covariates included in the model.
- B_0 represents the intercept.
- $B_1, B_2, \dots, B_k$ represent the estimated regression coefficients.

The covariates included in the propensity score model were selected based on theoretical considerations and previous evidence on factors influencing training participation and technical skill development. These included gender, age, education level, designation, curriculum coverage, practical exposure, hands-on learning opportunities, lecturer training manuals, institutional support, school-work mismatch, lecturer exam emphasis, and graduate training frequency.

The quality of the matching procedure was assessed using standardized mean differences (SMDs). The SMD was calculated as:

$$SMD = (X_{treated} - X_{control}) / \sqrt{[(s^2_{treated} + s^2_{control}) / 2]} \quad (2)$$

Where:

- $X_{treated}$ represents the mean value of a covariate among trained respondents.
- $X_{control}$ represents the mean value of a covariate among untrained respondents.
- $s^2_{treated}$ and $s^2_{control}$ represent the variances of the covariates in the two groups.

An SMD value below 0.10 was considered evidence of adequate balance. After matching, all covariates achieved SMD values below this threshold, with a mean SMD of 0.04 and a maximum SMD of 0.09, confirming that the matching procedure successfully reduced differences between the treatment and control groups.

The Average Treatment Effect on the Treated (ATT) was then estimated to determine the effect of regular EV training on technical knowledge and diagnostic confidence. The ATT was calculated as:

$$ATT = (1 / n_t) \sum (Y_i^1 - Y_i^0) \quad (3)$$

Where:

- Y_i^1 represents the observed outcome for respondent i who received EV training.
- Y_i^0 represents the estimated outcome for the same respondent if they had not received EV training, obtained from the matched control group.

- n_t represents the number of treated respondents.

Robust standard errors were estimated using bootstrap resampling with 1,000 iterations. The 95% confidence interval for the ATT estimate was calculated as:

$$95\% \text{ CI} = \text{ATT} \pm 1.96 \times \text{SE}$$

where **SE** represents the standard error of the estimated treatment effect. This approach provided robust estimates of the effect of regular EV training by accounting for observed differences between trained and untrained respondents.

Statistical Software

All statistical analyses were performed in R version 4.3.2 and IBM SPSS Statistics version 20. R was the main program used for propensity score matching and complex statistical analysis, along with packages *Matching*, *MatchIt*, *rbounds*, *psych*, and *ggplot2* for propensity score matching, sensitivity analysis, reliability assessment, and visualization. Data management, descriptive statistics, and basic inferential analyses were conducted using IBM SPSS Statistics version 20.

Model Validation and Quality Assurance

Propensity Score Model Validation

Treatment effects were estimated after validating the propensity score model to ensure equivalence of treatment and control groups in the matching process. The common support assumption was evaluated, and covariate balance diagnostics were used to assess model adequacy to a large degree. Standardized mean differences (SMDs) were used to evaluate covariate balance, with SMDs less than 0.10 indicating good balance between matched groups. After the matching procedure, all the covariates were within the recommended SMD values, indicating that the differences between the respondents with regular EV training and those without were mostly eliminated. In addition, the common support assumption was assessed by examining the overlap in the propensity score distributions of the treatment and control groups. The overlap observed showed that appropriate matches were found for almost all treated respondents, which confirmed the validity of the propensity score matching procedure.

Bootstrap Validation

Bootstrap validation (1,000 resampling iterations) was used to examine the robustness and stability of estimated treatment effects. Robust standard errors were computed using the bootstrap procedure, 95% confidence intervals were calculated, stability of the matching estimates were assessed and overfitting was avoided. For each bootstrap iteration ($b = 1, 2, \dots, 1000$), a bootstrap sample of size $N = 753$ was randomly drawn with replacement from the original dataset. The propensity score model was then re-estimated using the bootstrap sample, followed by the matching procedure and estimation of the corresponding treatment effect. This process was repeated 1,000 times to obtain a distribution of bootstrap ATT estimates.

The bootstrap estimate of the Average Treatment Effect on the Treated (ATT) was calculated as:

$$\text{Bootstrap Mean ATT} = (1/1000) \times \sum_{b=1}^{1000} \text{ATT}_b \quad (4)$$

where:

- ATT_b = treatment effect estimated from the b th bootstrap sample.
- 1000 = total number of bootstrap replications.

The bootstrap standard error was computed as:

- Bootstrap SE = $\sqrt{\sum_{b=1}^{1000} (\text{ATT}_b - \text{Bootstrap Mean ATT})^2 / (1000 - 1)}$

The 95% bootstrap confidence interval (CI) was obtained using the percentile method:

- 95% CI = [2.5th percentile of the bootstrap ATT estimates, 97.5th percentile of the bootstrap ATT estimates]
- Equivalently, 95% CI = $[\text{ATT}_{2.5\%}, \text{ATT}_{97.5\%}]$

where $\text{ATT}_{2.5\%}$ and $\text{ATT}_{97.5\%}$ denote the 2.5th and 97.5th percentiles of the empirical bootstrap distribution of the ATT estimates, respectively. This validation procedure provided robust estimates of the treatment effects and ensured that the reported results were stable, reliable, and not unduly influenced by sampling variability.

Ethical Considerations

This study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of the lead institution (Ref. No: IRID/EC2026/HS00162). All participants provided informed consent prior to participation. Data were anonymized and stored on secure servers accessible only to the research team. Results are reported in aggregate form only, with no individual-level data disclosed.

Methodological Limitations

Several methodological limitations should be considered when interpreting these findings. First, the study used a cross-sectional design that captures a state of EV competencies at one point in time. This design works well for evaluating existing skill gaps, but does not provide any temporal relationships or measure changes over time. Future research should use longitudinal designs to assess the changes in EV competencies across time and to examine the impact of training interventions. Secondly, the industry professionals (Other category, 39.4%) were overrepresented and technicians (16.3%) and academic staff (8.4%) were underrepresented in the sample. Propensity score matching was implemented to control for this imbalance when estimating treatment effects, but the non-representativeness of technicians who are directly involved in EV repair and maintenance may restrict the generalizability of the results for this group of technicians. Future studies should use more balanced sampling to have good representation for all profession groups.

Third, the study used self-reported measures of EV knowledge, confidence, and competency. Self-reported measures are often used for skills assessments but can have the

danger of social desirability, overestimation and/or underreporting. Future research should incorporate objective measures of EV competency, including practical tests for competency and/or certification exams or employer assessments to validate the findings. Fourthly, the study was geographically limited to the town of Kumasi in Ghana. The results are unlikely to be representative of other parts of Ghana or other nations because the city of Kumasi has one of the biggest automotive clusters in West Africa (Suame Magazine). Further studies are recommended to be conducted in other geographical areas and to compare the results to other contexts. Fifth, the study focused on graduate readiness and competency gaps but did not assess the training capacity of automotive institutions, the availability of EV training equipment, or the preparedness of instructors. Future research should examine these institutional and instructor factors to understand the systemic determinants of the identified skills gaps.

RESULTS AND DISCUSSION

Table 1: Demographic features of respondents

Variable	Category	Frequency (n)	Percent (%)
Gender	Female	49	6.5
	Male	704	93.5
	Total	753	100.0
Age (years)	18-25	603	80.1
	26-35	102	13.5
	36-45	48	6.4
	Total	753	100.0
Level of Education	BEng/BTech	423	56.2
	Diploma	137	18.2
	HND	166	22.0
	MEng/MTech	24	3.2
	MVTI	3	0.4
	Total	753	100.0
Designation	Graduate	270	35.9
	Lecturer	12	1.6
	Manager	22	2.9
	Other	297	39.4
	Service Advisor	3	0.4
	Supervisor	26	3.5
	Technician	123	16.3
	Total	753	100.0

Table 1 presents the demographic characteristics of the respondents, which revealed that most of them were male (704, 93.5%) and a few were female (49, 6.5%). Regarding age, the majority of the respondents were 18-25 years (603, 80.1%), whereas a few were 36-45 years (48, 6.4%). For educational qualification, the majority of the respondents had BEng/BTech qualifications (423, 56.2%), and a few of them had an MVTI qualification (3, 0.4%). Concerning designation, most of the respondents belonged to the 'Others' category (297, 39.4%), whereas few were Service Advisors (3, 0.4%)

Table 2: Content Validity Index (CVI) of the Survey Instrument

Section	No. of Items	I-CVI Range	S-CVI/Ave
Section A: Personal Information (Q ₁ -Q ₄)	4	0.90-1.00	0.95
Section B: Academic Preparation (Q ₅ -Q ₁₃)	9	0.80-1.00	0.92
Section C: Industry Expectations (Q ₁₅ -Q ₂₃)	9	0.80-1.00	0.93
Section D: Graduate Perspectives (Q ₂₄ -Q ₂₈)	5	0.80-1.00	0.91
Section E: Barriers and Competencies (Q ₂₉ -Q ₃₄)	6	0.85-1.00	0.92
Section F: Recommendations (Q ₃₅ -Q ₃₈)	4	0.85-1.00	0.94

The results of the content validity analysis as presented in Table 2 showed that the survey instrument had good content validity in all the sections. The Item Content Validity Index (I-CVI) ranged from 0.80 to 1.00 on the various parts of the questionnaire, reflecting high agreement among experts on the relevance and clarity of the items. The average method of the Scale Content Validity Index (S-CVI/Ave) ranged from 0.91 to 0.95, indicating sufficient content representativeness of the instrument, as per the recommended index of 0.80. The highest content validity, S-CVI/Ave of 0.95 and I-CVI range of 0.90-1.00, was obtained with Section A: Personal Information followed by Section F: Recommendations with an S-CVI/Ave of 0.94. Section C: Industry Expectations, with an S-CVI/Ave of 0.93, and Section B: Academic preparation with an S-CVI/Ave of 0.92 had an S-CVI/Ave of 0.93, and Section E: Barriers and Competencies had an S-CVI/Ave of 0.92. The lowest S-CVI/Ave value was for Section D: Graduate Perspectives (0.91), which is a very good content validity.

Table 3: Reliability Analysis of the Survey Instrument Sections

Section	No. of Items	Cronbach's Alpha	95% CI Lower	95% CI Upper
Section B: Academic Preparation (Q ₅ -Q ₁₃)	9	0.82	0.79	0.85
Section C: Industry Expectations (Q ₁₅ -Q ₂₃)	9	0.85	0.82	0.88
Section D: Graduate Perspectives (Q ₂₄ -Q ₂₈)	5	0.76	0.72	0.80
Section E: Barriers and Competencies (Q ₂₉ -Q ₃₄)	6	0.78	0.74	0.82
Section F: Recommendations (Q ₃₅ -Q ₃₈)	4	0.71	0.67	0.75

The results of the reliability analysis for the different sections of the survey tool (Table 3) showed that all the questionnaire domains had acceptable to good internal consistency. Section C: Industry Expectations had the highest reliability level with a Cronbach's alpha coefficient of 0.85 (95% CI: 0.82-0.88) while Section B: Academic Preparation had an alpha coefficient of 0.82 (95% CI: 0.79-0.85), indicating consistency of items measuring these constructs. The Cronbach's alpha for Section E: Barriers and Competencies was 0.78 (95% CI: 0.74-0.82), and for Section D: Graduate Perspectives it was 0.76 (95% CI: 0.72-0.80), both of which were acceptable. The total internal consistency of Section F: Recommendations ($\alpha = 0.71$, 95% CI: 0.67-0.75) was also adequate, although the lowest of the sections, with a minimum level to be recommended of 0.70.

Table 4: Current Level of EV-Specific Awareness, Technical Knowledge, and Practical Competency

Variable	Category	Count	Proportion (%)	95% CI Lower (%)	95% CI Upper (%)
Knowledge/skills in EV fault diagnosis	No	385	51.1	47.6	54.7
	Yes	368	48.9	45.3	52.4
Confidence in diagnosing EV systems	Moderately confident	250	33.2	29.9	36.6
	Not confident at all	167	22.2	19.4	25.3
	Slightly confident	182	24.2	21.3	27.4
	Very confident	154	20.5	17.7	23.5
Diagnostic tools/software used	Advanced EV diagnostic platforms	60	8.0	6.2	10.1
	Basic OBD-II scanner	223	29.6	26.5	33.0
	Manufacturer-specific tools	115	15.3	12.9	18.0
	None	355	47.1	43.6	50.7
Familiarity with EV error codes	Familiar with common codes	239	31.7	28.5	35.1
	Highly proficient	49	6.5	5.0	8.5
	Not familiar	366	48.6	45.1	52.2
	Somewhat familiar	99	13.1	10.9	15.8

As shown in Table 4, the overall awareness, technical knowledge, and practical competence of respondents to electric vehicles (EVs) is relatively low. Slightly more than half of the respondents reported having no knowledge or skills in EV fault diagnosis (51.1%, 95% CI: 47.6% to 54.7%), while 48.9% (95% CI: 45.3% to 52.4%) indicated that they possessed such knowledge and skills. Regarding confidence in diagnosing EV systems, the largest proportion of respondents were moderately confident (33.2%, 95% CI: 29.9% to 36.6%), followed by those who were slightly confident (24.2%, 95% CI: 21.3% to 27.4%) and not confident at all (22.2%, 95% CI: 19.4% to 25.3%). High levels of diagnostic confidence with EV systems were uncommon, with only one-fifth of respondents confirming they were very confident in their ability to diagnose these systems (20.5%, 95% CI: 17.7% to 23.5%). Likewise, there was limited use of EV diagnostic tools and understanding of EV error codes. Nearly half of the respondents reported using no diagnostic tools or software for EVs (47.1%, 95% CI: 43.6% to 50.7%), whereas 29.6% (95% CI: 26.5% to 33.0%) relied on basic OBD-II scanners, 15.3% (95% CI: 12.9% to 18.0%) used manufacturer-specific diagnostic tools, and only 8.0% (95% CI: 6.2% to 10.1%) used advanced EV diagnostic platforms. In terms of familiarity with EV error codes, almost half of the respondents were not familiar with EV error codes (48.6%, 95% CI: 45.1% to 52.2%), while 31.7% (95% CI: 28.5% to 35.1%) were familiar with common codes. A smaller proportion reported being somewhat familiar (13.1%, 95% CI: 10.9% to 15.8%), and only 6.5% (95% CI: 5.0% to 8.5%) indicated that they were highly proficient.

Table 5: Distribution of Propensity Scores

Treatment Group	n	Min	Q ₁	Median	Mean	Q ₃	Max
Control	638	0.03	0.12	0.18	0.22	0.28	0.82
Treated	115	0.08	0.24	0.36	0.39	0.52	0.85

Table 5 shows the distribution of the propensity score before matching. The mean propensity score was 0.22, the median was 0.18, and the interquartile range (IQR) for the control group (n = 638) was 0.12 to 0.28, meaning that the majority of participants in the control group had a relatively low probability of receiving the treatment. The treated group (n = 115) had higher mean, median, and interquartile range scores (0.39, 0.36, 0.24-0.52) that indicated greater likelihood of treatment assignment. The treated group generally had higher propensity scores than the control group, but all of the scores in the two groups had ranges in common (between 0.08 and 0.82 for the control group and 0.08 and 0.85 for the treated group), which suggests a common support region. This overlap implies that it is possible to create propensity score matching because similar individuals who would have been treated and similar individuals who would not have been treated could be identified by having similar estimated probabilities of treatment assignment.

Table 6: Specific Technical, Diagnostic, and Occupational Safety Skill Deficiencies

Survey Question / Variable	Response Category	Frequency (N)	Weighted Score (%)
Knowledge/Skills in EV Diagnosis	No	385	51.1
	Yes	368	48.9
Confidence in Diagnosing EV Systems	Moderately confident	250	33.2
	Slightly confident	182	24.2
	Not confident at all	167	22.2
	Very confident	154	20.5
Diagnostic Tools/Software Used	None	355	47.1
	Basic OBD-II scanner	223	29.6
	Manufacturer-specific tools	115	15.3
	Advanced EV diagnostic platforms	60	8.0
Adequate Skills to Repair EV Technologies	No / Few are certified	~400	~53.1
	Yes / All are certified	~350	~46.9
Components Least Confident Repairing	Battery packs	~240	31.9
	Power electronics (inverter, converter)	~210	27.9
	Charging systems	~165	21.9
	Thermal management systems	~135	17.9
Emerging Tech Graduates Least Prepared For	AI-driven energy management	~225	29.9
	Solid-state batteries	~190	25.2
	Smart charging networks	~170	22.6
	Advanced thermal management	~165	21.9
Major Barriers to EV Repair & Maintenance	High-voltage safety risks discourage graduates	617	82.0
	High cost of training and equipment	565	75.0
	Inadequate curriculum content of EV technology	515	68.4
	Limited graduate knowledge	452	60.0
	Lack of industry standards and policies	414	55.0
	Other	98	13.0

Table 6 shows that respondents' technical, diagnostic and occupational safety skills were found to be significantly lacking in terms of electric vehicle (EV) technologies. Over half of respondents indicated that they do not have EV diagnosis knowledge and skills (51.1%), while 48.9% indicated they have such knowledge and skills in EV diagnosis. In terms of confidence in diagnosing EV systems, the majority were moderately confident (33.2%) followed by very confident (20.5%), not confident at all (22.2%) and slightly confident (24.2%). In addition, nearly half of the respondents (47.1%) said they were not using any diagnostic tools or software, and only 8.0% were able to access advanced diagnostic platforms for EVs. Additionally, about 53.1% said that they would not have enough skills or certification to fix EV technologies, meaning a significant share of graduates is not equipped to perform EV maintenance and repair duties. The findings also indicate certain areas where respondents have the highest technical difficulties. Respondents were least confident in repairing Battery packs (31.9%), Power electronics including Inverters and Converters (27.9%), Charging systems (21.9%) and Thermal management systems (17.9%). As it comes to emerging technologies, respondents answered the least ready for solid-state batteries (25.2%), followed by smart charging networks (22.6%), advanced thermal management systems (21.9%) and AI-powered energy management systems (29.9%). Graduates were most concerned about the safety risks associated with high voltage systems (82.0%), the high cost of training and equipment (75.0%), inadequate EV curriculum content (68.4%), lack of understanding regarding the knowledge of EVs (60.0%), and lack of industry standards and policies (55.0%). Only 13.0% identified other barriers.

Table 7: Overall EV Repair Knowledge - Beginner to Expert

Group / Estimate	N	Mean	SD / SE	95% Confidence Interval	t statistic (df)	p-value
Treated	112	2.67	0.92 (SD)	[2.51, 2.83]	-	-
Control	112	2.24	0.88 (SD)	[2.08, 2.40]	-	-
ATT (Treated – Control)		0.43	0.12 (SE)	[0.19, 0.67]	3.58 (222)	0.0004

The results in Table 7 demonstrate a statistically significant and meaningful positive effect of regular EV training on overall repair knowledge. The treated group that received regular training scored a mean of 2.67 (on a 1 to 4 scale with Beginner to Expert) while the control group scored a mean of 2.24, giving an Average Treatment Effect on the Treated (ATT) of 0.43 points. This difference is highly statistically significant ($p < 0.001$, $t(222) = 3.58$), and the 95% CI for the ATT is (0.19, 0.67), which is all positive; thus, the difference is not due to chance. From a practical standpoint, this 0.43-point gain is significant, bringing the average respondent from the lower end of the "Intermediate" category into the upper end, which indicates that ongoing training provides a valuable improvement in EV repair knowledge. This estimate is accurate because the standard error is relatively small (0.12), suggesting that the effect is consistent across the matched sample.

Table 8 reports the balance diagnostics before and after propensity score matching with standardized mean differences (SMDs). Before matching, there were significant differences in the treatment and control groups for a handful of covariates, with the SMD ranging from 0.09 to 0.42, and an average of 0.24. There were significant differences in baseline between the two groups for the following items: practical exposure (Q_9) (SMD =

0.42), hands-on learning (Q_{12}) (SMD = 0.38), curriculum coverage (Q_5) (SMD = 0.35), and graduate training frequency (Q_{33}) (SMD = 0.33). School-work mismatch (Q_{24}), education (SMD = 0.21), and age (SMD = 0.18) also showed moderate imbalances, whilst relatively smaller differences were found for lecturer training manuals (Q_{11}) (SMD = 0.29), lecturer exam emphasis (Q_{28}) (SMD = 0.11), and gender (SMD = 0.12). After propensity score matching, there was a significant improvement in the balance between the treatment and control groups. The matched SMD values ranged from 0.01 to 0.08 with the mean matched SMD of 0.04 and a maximum of 0.09, which all were below the commonly accepted value of 0.10 for sufficient covariate balance. Specifically, designation (SMD = 0.02) and school-work mismatch (SMD = 0.01) had the best balance, whereas the highest matched SMD (0.08) was hands-on learning and still in an acceptable range.

Table 8: Balance Diagnostics (Standardised Mean Differences)

Covariate	SMD (Unmatched)	SMD (Matched)	Balance Achieved
Gender (Female vs. Male)	0.12	0.03	✓
Age (18-25 vs. 26+)	0.18	0.04	✓
Education (HND vs. Degree)	0.21	0.05	✓
Designation (Technician vs. Other)	0.14	0.02	✓
Curriculum coverage	0.35	0.07	✓
Practical exposure	0.42	0.06	✓
Hands-on learning	0.38	0.08	✓
Lecturer training manuals	0.29	0.06	✓
Institutional support	0.15	0.03	✓
School-work mismatch	0.09	0.01	✓
Lecturer exam emphasis	0.11	0.03	✓
Graduate training frequency	0.33	0.05	✓
Mean SMD	0.24	0.04	
Maximum SMD		0.09	

Table 9: Contextually appropriate, evidence-based strategies can be developed and implemented to address the identified EV skills

Variable	Response Category	Frequency (N)	Percent (%)
Additional training to improve EV repair skills	Regular repair and maintenance of EV systems	325	43.2
	Diagnostics and troubleshooting of EV	229	30.4
	Power electronics troubleshooting	84	11.2
	Other	59	7.8
	High-voltage safety and protocols	29	3.9
	Charging infrastructure maintenance	27	3.6
Curriculum area universities should strengthen most	Industry internships	287	38.1
	Collaboration with EV companies	213	28.3
	EV-specific courses	205	27.2
	Interdisciplinary projects	48	6.4

Most effective way academia can improve graduate readiness	Increase lab-based training	234	31.1
	Strengthen industry partnerships	227	30.1
	Introduce specialized EV courses	210	27.9
	Encourage applied research projects	82	10.9
Collaboration method to most benefit graduate readiness	Internships and apprenticeships	496	65.9
	Joint research projects	104	13.8
	Industry-sponsored competitions	83	11.0
	Guest lectures by industry experts	70	9.3
Most valuable competency for EV engineers in the next 5-10 years	AI and machine learning applications	372	49.4
	Advanced battery technology expertise	181	24.0
	Sustainable design and recycling	121	16.1
	Smart grid and charging integration	79	10.5

Table 9 shows that respondents identified key strategies for improving EV skills development and graduate readiness. For additional training needs, the majority of respondents indicated that regular repair and maintenance of EV systems (43.2%) was the most important area for improvement, while few identified charging infrastructure maintenances (3.6%) as a priority. Regarding curriculum areas universities should strengthen, most respondents selected industry internships (38.1%), whereas few recommended interdisciplinary projects (6.4%). In terms of improving graduate readiness, the majority supported increased lab-based training (31.1%), while few preferred encouraging applied research projects (10.9%). For collaboration methods that would most benefit graduates, most respondents identified internships and apprenticeships (65.9%), whereas few selected guest lectures by industry experts (9.3%). Finally, concerning the most valuable future competency for EV engineers, most respondents considered AI and machine learning applications (49.4%) as the most important skill area, while few identified smart-grid and charging integration (10.5%) as the most critical competency.

Table 10: Propensity Score Matching Results for Confidence in Diagnosing EV Systems

Group / Estimate	N	Mean	SD / SE	95% Confidence Interval	t statistic	df	p-value
Treated	112	2.91	0.85 (SD)	[2.75, 3.07]	-	-	-
Control	112	2.52	0.91 (SD)	[2.35, 2.69]	-	-	-
ATT (Treated – Control)		0.39	0.11 (SE)	[0.17, 0.61]	3.55	222	0.0005

The propensity score matching results in Table 10 indicate a statistically significant positive effect of regular EV training on respondents' confidence in diagnosing EV systems. The treated group, comprising respondents who received regular EV training, recorded a higher mean confidence score of 2.91 compared with 2.52 for the matched control group, resulting in an Average Treatment Effect on the Treated (ATT) of 0.39 points. This difference was statistically significant ($t(222) = 3.55$, $p = 0.0005$), providing strong evidence that regular training improves diagnostic confidence. Furthermore, the 95% confidence interval for the ATT ranged from 0.17 to 0.61, which lies entirely above zero, confirming that the observed

improvement is unlikely to have occurred by chance. The relatively small standard error of 0.11 indicates a precise estimate of the treatment effect.

The Prevalence of EV Knowledge and Skills Deficiencies

The findings show low awareness and technical knowledge, and in general a low level of competency in the practices of the respondents in the field of EVs. Less than half of respondents had knowledge and skills in EV fault diagnosis (51.1%), and only 20.5% felt very confident in diagnosing EV systems. These results are consistent with previous studies in Sub-Saharan Africa. [3, 9] revealed that automotive graduates and technicians in the region are not exposed to the latest automotive technologies such as EVs, hybrid systems, and digital diagnostics. Likewise, [10] revealed that technical education in sub-Saharan Africa is mainly geared towards the traditional internal combustion engine (ICE) repair field, which is not in line with industry demand. This lack of confidence and familiarity with EV error codes is especially alarming. Familiarity with basic EV error codes was found in 31.7% of all respondents, and 6.5% were very knowledgeable. The results align with those of [18, 20], who reported that automotive technicians in developing countries lack the skills required to service new EV technologies, such as the use of digital diagnostic tools. This deficiency is compounded by the limited adoption of diagnostic tools and software: 47.1% of respondents said they were using none of these diagnostic tools and 8.0% had access to advanced EV diagnostic platforms. The lack of tool familiarity is indicative of the low quality of training equipment in the Ghanaian automotive institutions, which is also reported by [4, 19]. The results also identify specific technical areas that graduates are less prepared. The batteries (31.9%) and power electronics (27.9%) like inverters and converters were the components that respondents were least confident of repairing. This aligns with the literature that shows the high-voltage electrical systems, traction batteries and battery management systems, and power electronics are important EV competencies that are poorly addressed by conventional automotive training programs [1, 2]. Emerging technologies that were least prepared for included AI-driven energy management systems (29.9%) and solid-state batteries (25.2%), which highlights the growing speed of technological development and the challenge of having curricula that are current.

Barriers to EV Competency Development

High-voltage safety risks discouraging graduates (82.0%), the high cost of training and equipment (75.0%), inadequate EV curriculum content (68.4%), limited graduate knowledge (60.0%), and lack of industry standards and policies (55.0%), were the most frequently reported barriers to EV repair and maintenance. The findings align with the study of [19], which revealed that outdated curriculum in TVET, lack of training equipment, and a gap between the needs of the industry and the competencies of graduates are significant challenges to the workforce development for EVs. Likewise, [20] reported that high training expenses and equipment costs, and level of exposure to the EV industry, limit EV competencies in developing countries. One of the notable results is the 82.0% of those surveyed who believed that high voltage safety issues were a significant challenge. This is an indication of the real safety issues of working with high voltage EV systems, a requirement of such a system is specialized training which is not always available in Ghanaian automotive training institutions and garages, and specialized equipment. Lack of complete safety

training and procedures discourages EV students from entering the EV repair business and can even put students at risk if they attempt repairs without proper training. [17, 18] have highlighted the importance of having a standardised EV safety training course as a prerequisite to workforce readiness due to the safety gap. The industry standards and policies (55.0%) are also a challenge to EV competency development. Lack of regulatory frameworks, requirements, and industry standards makes it difficult for training providers and employers to know what knowledge and skills are needed to undertake EV repair and maintenance work. This agrees with [24] who observed that Ghana has not yet been able to implement comprehensive policies and standards on the adoption, maintenance and servicing of EVs.

The Impact of Regular EV Training on Knowledge and Confidence

The findings from the propensity score matching analysis are robust and indicate that there are positive impacts of EV training on repair knowledge and diagnostic confidence. The mean knowledge score was significantly higher for the treated group (2.67) than for the control group (2.24) with an Average Treatment Effect on the Treated (ATT) of 0.43 ($p < 0.001$). Similarly, there was a higher mean confidence score for the treated group (2.91) than for the control group (2.52), and an ATT of 0.39 ($p = 0.0005$). These results are in line with the competency training literature. The competency-based training methods have been shown to have a significant impact on the improvement of technical competencies and the behaviour of teachers [3]. Likewise, for quality training delivery in vocational education, building trainer competencies and skills is an essential factor according to [4]. To build upon these results, the present study measures the impact of regular EV training on knowledge and confidence, offering empirical evidence that training interventions can have a meaningful impact on EV workforce preparedness. This should be pointed out in terms of its practical implications. The average respondent would move from the low end of the "Intermediate" category to the high end with a 0.43-point boost in knowledge score, indicating that regular training significantly improves EV repair knowledge. A 0.39-point rise in confidence is also significant in terms of the ability to diagnose.

CONCLUSION AND RECOMMENDATIONS

The current study examined the preparedness of the automotive graduates and skills gaps in automotive industry for electric vehicle (EV) repair and maintenance in Kumasi, Ghana. The results indicate that there are significant gaps in EV knowledge, diagnosis and competencies among graduates and professionals in the automotive field. The results show there is a significant mismatch between the skills required in the changing automotive industry and the skills of the workforce. This discussion is presented with reference to literature, interpretation of the findings, implications for Ghana and implications for policy, curriculum and practice.

Conclusion

This study evaluated the readiness of automotive graduates and competence gaps of EV repair and maintenance in Kumasi, Ghana. The results indicate significant gaps in

understanding, diagnostic abilities, and hands-on experience in the field of EVs among automotive students and practitioners. Over half of the respondents reported not knowing/being skilled with EV fault diagnosis and only one-fifth reported high confidence in EV system diagnosis. Limited diagnostic use and lack of knowledge of EV error codes were likewise reported, with almost half using no diagnostic tools and almost half having no knowledge of EV error codes. Graduates were least prepared in specific technical areas such as battery packs, power electronics and charging systems, and emerging technologies like AI-based energy management and solid-state batteries. High voltage safety concerns, expensive training and equipment, EV curriculum content, and limited graduate knowledge, as well as industry standards and policies were cited as the most common barriers to EV competency development. The findings from the propensity score matching analysis are significant and support the positive impact of the regular EV training on repair knowledge and diagnostic confidence. Participants who were provided with regular EV training had significantly higher knowledge and confidence scores. The results highlight the need for sustained systematic EV training of automotive graduates and professionals. The responses revealed a number of strategies to enhance skills development and graduate readiness for EVs such as frequent repair and maintenance training, industry internships, partnerships with EV companies, increased lab-based training, and improved industry partnerships. Internships and apprenticeships were the most desired approach to collaboration, and the most desired future competency was AI and machine learning applications. The study adds to the existing body of work on EV workforce development by offering empirical evidence from Ghana, estimation of the impact of EV training through propensity score matching and EV specific competency gaps and training priorities.

The findings have a significant policy and practice implication as well as a curriculum development implication as there is a need for new automotive curriculum, investment of training equipment and facilities, industry standard for repair and maintenance of EVs and validation of training skill of the workforce by certification system. It is important to note, however, that the findings should be interpreted in the context of the limitations which include the cross-sectional design, the geographical limitation to Kumasi and the use of self-reported measures, as the sample was imbalanced. For the purpose of future validation and expansion of the findings, future research should use more balanced sampling strategies, objective measures of competency and incorporate a broader geographic scope. Electric mobility transformation in Ghana is inconceivable without competent workforce to service and maintain EVs. The results of this study reveal a significant competency gap, highlighting the need for strategic interventions to enhance EV repair and maintenance skills. Through investments in training, curriculum updates, and partnerships with industry, Ghana can develop a skilled workforce to facilitate EV adoption and support sustainable transport sector transition.

Recommendations

Enhancing Graduate Readiness

Participants identified a number of strategies for strengthening EV skills and graduate readiness. For additional training needs, regular repair and maintenance of EV systems (43.2%) and diagnostics and troubleshooting (30.4%) were the most frequently cited priorities. The most frequent answers for the curriculum enhancements that universities

should focus on were industry internships (38.1%), collaboration with EV companies (28.3%), and EV-specific courses (27.2%). The top-three recommendations for enhancing graduate readiness included more laboratory training (31.1%), better industry connections (30.1%) and specialized EV courses (27.9%). Internships and apprenticeships (65.9%) ranked as the most valuable collaboration method and AI and machine learning applications (49.4%) ranked as the most valuable future competency. The recommendations are consistent with larger body of literature on workforce development for emerging technologies. [20] highlighted the importance of industry-institution collaborations and practical training methods for strengthening EV industry workforce readiness. [19] advocated for changes to the curriculum, investments in equipment, and policy supports to enhance EV repair and maintenance skills. The high uptake of internships and apprenticeships (65.9%) suggests that workplace learning and experience are relevant, a finding aligned with the apprenticeship arrangements that have proven successful in other technical vocational contexts [2]. The focus on AI and machine learning applications (49.4%) as the most valuable future competency is significant. This is due to the increasing significance of digital skills in the automotive sector, where connected and autonomous vehicles are increasingly being propelled by an AI-based system [5, 11]. The discovery implies that the development of the EV workforce requires more than just the mechanical and electrical skills of the past; it also needs to encompass new and developing digital skills.

Implications for Ghana's Automotive Sector and Policy

The findings have important implications for Ghana's automotive sector and policy. First, the significant competency gaps revealed suggest that Ghana's workforce is not well equipped to make a shift to the electric mobility industry. This aligns with the findings of [24], which revealed that Ghana has many problems in shifting to EVs, including the lack of skilled technicians. If nothing is done, the spread of EVs in Ghana will be limited because of the lack of competent people to service and maintain the vehicles. Secondly, the positive outcomes of regular EV training for knowledge and confidence give a loud and clear policy message: investment in EV training programmes is a necessity to build a skilled workforce. This is in line with the recommendations of [19, 20], who called for training, equipment, and curriculum changes to prepare for the EV transition. Based on the findings, it is recommended that training should emphasize the need to practice EV systems, diagnostic tools, and safety procedures regularly in a hands-on manner. Third, the challenges identified, especially the high cost of training and equipment, insufficient curriculum material, and a lack of industry standardization, signal the need for systems-level interventions. This includes, but is not limited to, updating the automobile curriculum to include EV content, investing in training equipment and facilities, creating industry standards and training for EV repair and maintenance, and creating certification programs to validate workforces' skills and knowledge. These recommendations align with those of [4], who highlighted the importance of establishing trainer capabilities and laying the groundwork for quality trainer training delivery.

Future Research Directions

This study has identified a number of suggestions for further research based on the results and the limitations. First, there is a need for longitudinal studies to monitor the evolution

of EV competencies over time and to evaluate the success of training interventions, curriculum reforms, and policy changes. This type of research would give sound evidence about what is effective in developing EV workforce capability. Secondly, comparative studies are required to compare the competency gaps in EVs in various regions, countries and training systems. This would assist in determining practices and factors that relate to EV workforce readiness development. Third, research incorporating objective assessments of EV competency would yield more robust evidence of the technical skills and competencies needed for EV repair and maintenance. This would help to complement the self-reported measures used in the present study.

Fourth, there is a need for research on institutional and instructor variables that affect EV competency development, such as training equipment, instructor preparation, and incorporation of EV topics into curricula. This research will help to illuminate systemic barriers and enablers to EV workforce development. Finally, future studies should focus on the role of informal apprenticeship systems, which are widely used in Ghana's automotive industry in EV competency development. The competencies that informal apprentices learn (or not) are key to designing inclusive training strategies.

Contribution to the Literature

This study contributes to the literature on EV workforce development in several ways. It offers empirical evidence from a country with limited EV uptake but great potential for electric mobility, such as Ghana. This study is different from other skills gap analyses that examine higher education skills for employability or soft skills, as it aims to singularly capture the disconnect between the skills of graduates and industry needs for an EV transition. This is especially relevant because of the quick expansion of the automotive industry in Sub-Saharan Africa, and the necessity for a capable labour force to aid sustainable transportation systems. Second, the study employs propensity score matching to assess the causal impact of EV training on knowledge and confidence, and offers strong evidence that training can optimise workforce readiness. This methodological approach can be considered new in the field of EV skills assessment, where most of the studies in the past have been descriptive, using simple comparisons. Third, the study highlights areas of competency gaps and training needs that can guide curriculum and policy development, and practice. The findings provide actionable recommendations for automotive training institutions, industry stakeholders, and policymakers seeking to strengthen EV repair and maintenance competencies. Regular practical training, industry internships, and industry collaboration are highlighted, showing the need for a collaborative approach to match education with industry demands.

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