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Enhancing Healthcare Delivery Through Continuous Medical Education: A Study On Skill Advancement Among Paramedical Personnel

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Abstract:-
Aim/Purpose:- The aim of this descriptive research was to examine the impact of continuous medical education (CME) on skill enhancement among paramedical personnel and its role in improving healthcare delivery. Outcome:- The study found that CME programs significantly enhance the skills of paramedical staff, leading to better healthcare services. The results indicated a strong positive relationship between CME participation and skill advancement. Goodness-of-fit indices (GFI, AGFI, NFI, TLI) showed satisfactory values (>0.90), confirming the model's reliability. Structural Equation Modeling (SEM) confirmed the direct and indirect effect on the outcome variable skill advancement among the paramedical personnel.
Research Methodology/Design/Approach:- A closed-ended questionnaire was used to gather responses from paramedical professionals. Statistical Techniques:- Both descriptive and inferential statistics were applied, with a sample size of 500 using stratified random sampling. Tools such as Factor Analysis, Exploratory Factor Analysis (EFA), and SEM were used to analyze direct and indirect effects. Social Relevance:- The findings can benefit healthcare institutions and policymakers in designing effective CME programs to improve paramedical training, ultimately enhancing patient care. Generalization:- The results are applicable not only to the studied population but also to other regions, as skill development in healthcare is a universal need. Novelty:- This research contributes new insights into how continuous education improves paramedical skills, a less explored area in healthcare studies. Type of Research:- This is a descriptive research study based on collected survey data.

Keywords: *Continuous Medical Education (CME), paramedical personnel, skill advancement, healthcare delivery, training programs, medical training, healthcare improvement.*

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I. Introduction:

Continuous Medical Education (CME) plays a crucial role in upgrading the competencies of paramedical personnel, who form the backbone of healthcare delivery systems. While physicians often receive mandated training, paramedical staff frequently face gaps in structured skill development programs despite their frontline responsibilities. This study investigates how systematic CME interventions enhance technical proficiency, decision-making abilities, and service quality among nurses, technicians, and allied health workers. By analyzing training outcomes across multiple healthcare settings, the research identifies optimal educational approaches that translate into improved patient care metrics. The findings demonstrate that targeted CME not only bridges critical skill deficiencies but also fosters professional growth and team-based healthcare efficiency. Particularly in resource-limited environments, the study reveals how tailored training modules can overcome infrastructure and accessibility challenges. These evidence-based insights offer healthcare administrators a framework to design equitable CME programs that align with evolving clinical demands. Furthermore, the research establishes measurable correlations between continuous learning investments and enhanced healthcare outcomes, providing policymakers with actionable data for workforce development strategies. Ultimately, this investigation contributes to global efforts to strengthen health systems through sustainable paramedical education models that ensure quality care delivery across diverse populations.

II. Review Of Literature:

A study on skill-based educational training for ambulance personnel in South India demonstrated significant improvements in neonatal transport outcomes. Post-intervention, there was a notable reduction in hypothermia, hypoglycemia, and NICU stay duration, highlighting the effectiveness of targeted educational interventions(Kalyan et al., 2024). Continuous training ensures paramedics are equipped to handle diverse medical emergencies, thereby enhancing their role in pre-hospital care(Theodore, 2023) One of the most critical factors influencing the effectiveness of CME is the design of the educational content. Structured and focused programs that emphasize skill practice and real-world application have been shown to improve performance in key resuscitation areas such as airway management, intravenous (IV) insertion, and patient assessment (Lorenzo & Abbott, 2007). Research on paramedic airway management found that a 10-hour intensive education session significantly improved intubation success rates from 68% to 75% (Carter et al., 2022). Similarly, a focused continuing education program for US Army Medics improved skill performance in areas such as bleeding control and patient assessment (Lorenzo & Abbott, 2007). The content should also be evidence-based and aligned with current clinical guidelines. This ensures that paramedics are updated on the latest practices and can apply their knowledge in real-life scenarios (Harunavamwe & Mnqayi, 2021). Simulation-based training (SBT) has emerged as a highly effective method for enhancing paramedical skills. Simulation provides a low-risk environment where paramedics can practice high-acuity, low-occurrence events without compromising patient safety (Bell, 2024) . Studies have shown that SBT improves procedural success, error identification, and decision-making skills (Bienstock et al., 2022). For instance, a systematic review of SBT in paramedic education highlighted its effectiveness in improving airway management and general assessment and treatment skills (Bienstock et al., 2022). The fidelity of simulation, or how closely it mirrors real-life scenarios, also plays a role in learning outcomes. High-fidelity simulations, particularly those incorporating manikins and realistic case scenarios, have been shown to enhance skill retention and performance (Bienstock et al., 2022). Active learning strategies, such as case discussions, problem-solving exercises, and hands-on practice, are essential for reinforcing learning and improving competencies. A study on focused diagnostic ultrasound training for paramedics demonstrated that interactive and practical sessions significantly improved their ability to acquire and interpret images (Brooke et al., 2012). Similarly, the use of workbooks and low-cost simulation tools in continuing education programs has been shown to enhance engagement and skill development (Lindquist et al., 2020). Interprofessional simulations, which involve collaboration between paramedics and other healthcare professionals, have also been shown to improve teamwork, communication, and patient safety (Lehto et al., 2024). Feedback and debriefing are critical components of effective CME. Debriefing sessions after simulation training allow paramedics to reflect on their actions, identify errors, and improve their decision-making skills (Konzelmann, 2024) (Elsenbast et al., 2024). A study on interprofessional simulations found that participants valued debriefing as a key component of their learning experience, as it provided opportunities for constructive feedback and self-reflection (Lehto et al., 2024). Timely and specific feedback is also important for skill development. For example, a study on paramedic intubation success rates found that feedback during training sessions helped reduce the number of attempts per patient, indicating improved judgment and skill (Carter et al., 2022). The accessibility and flexibility of CME programs are key factors influencing their effectiveness. Paramedics often face challenges such as limited time, geographic constraints, and high workloads, which can hinder their participation in traditional classroom-based programs (Adefuye et al., 2020) (Ross & Shannon, 2023). To address these barriers, many organizations have adopted blended learning approaches that combine online modules with hands-on training (Knox et al., 2014) (Lindquist et al., 2020). For example, a study on continuing education for paramedics in India highlighted the success of icon-based video instruction and e-learning modules, which allowed participants to access training materials at their convenience (Lindquist et al., 2020). Similarly, the use of virtual reality (VR) and mixed reality (MR) technologies has been explored as innovative approaches to enhance accessibility and engagement in CME programs (Elsenbast et al., 2024) (Hérault, 2024). Organizational support is a critical enabler of effective CME. Employers play a key role in providing resources, such as training equipment, dedicated learning time, and access to expert facilitators (Hobbs et al., 2021) (Bryant et al., 2023). A study on paramedic CPD in Australia found that organizational support, including access to training materials and opportunities for self-directed learning, significantly influenced engagement and skill development (Hobbs et al., 2021). Additionally, the availability of qualified facilitators and instructors is essential for delivering high-quality training. A study on simulation-based training emphasized the importance of faculty development, particularly in the areas of debriefing and scenario design, to ensure the effectiveness of SBT programs (Konzelmann, 2024). Paramedics' motivation to engage in CME is influenced by a combination of personal and professional factors. A study on paramedic CPD in the UK found that personal motivations, such as the desire for clinical/professional improvement and a sense of professional accountability, were key drivers of engagement (Handyside & Watson, 2024). Additionally, fear of failing to meet professional standards or losing registration has been identified as a motivator for some paramedics (Hobbs et al., 2021). Organizational factors, such as recognition and incentives, can also enhance motivation. For example, a study on CPD in Ireland found that paramedics preferred practical training scenarios and simulation-based activities, which were seen as more relevant and engaging than traditional classroom-based learning (Knox et al., 2014). Interprofessional collaboration is an increasingly important aspect of healthcare education. Paramedics often work in teams with other healthcare professionals, and the ability to communicate and coordinate effectively is critical for patient care. A study on interprofessional simulations found that paramedics who participated in these sessions reported improved teamwork and communication skills, as well as a better understanding of other professionals' roles (Lehto et al., 2024). Interprofessional simulations also provide opportunities for paramedics to practice decision-making and problem-solving in realistic, high-pressure scenarios. This approach has been shown to enhance both technical and non-technical skills, such as leadership and situation awareness (Lehto et al., 2024). The use of technology in CME has expanded significantly in recent years, offering new opportunities for innovative and effective training. Virtual reality (VR) and mixed reality (MR) technologies, for example, provide immersive learning experiences that simulate real-life scenarios, allowing paramedics to practice high-stakes procedures in a safe environment (Elsenbast et al., 2024) (Hérault, 2024). A study on VR training for paramedics found that participants reported high levels of engagement and perceived improvement in their ability to handle emergency situations (Hérault, 2024). Other technologies, such as interactive video training and e-learning platforms, have also been shown to enhance accessibility and flexibility in CME programs. These tools allow paramedics to access training materials at their convenience, reducing barriers such as geographic location and time constraints (Lindquist et al., 2020) (Hérault, 2024). Finally, the effectiveness of CME programs should be regularly evaluated to ensure they meet their intended goals. A study on the evaluation of continuing education programs for EMS personnel found that a comprehensive evaluation framework, such as the Kirkpatrick Model, can provide valuable insights into the impact of training on knowledge, behavior, and patient outcomes ("Evaluating the Effectiveness of Continuing Education at Emergency Medical Services", 2022). The framework includes four levels of evaluation: reaction, learning, behavior, and results. For example, a study on the effectiveness of a community paramedic short course used a combination of pre- and post-test evaluations to assess improvements in knowledge, skills, and confidence. The results showed significant gains in all three areas, particularly in skills that were not traditionally taught in paramedicine, such as falls assessments and troubleshooting specialist equipment (Ross & Shannon, 2023).

Objectives:-

1. assess how the effectiveness of CME programs contributes to the knowledge retention and application performance (KRAP) among paramedical staff.
2. To investigate the mediating role of Skill Advancement and Application in the relationship between CME effectiveness and practical outcomes such as improved service delivery and patient care.
3. To examine the impact of various continuous medical education (CME) modules on the overall effectiveness of CME programs among paramedical personnel
4. To propose evidence-based strategies to optimize CME programs for enhancing both short-term skills and long-term professional development of paramedical personnel in the healthcare sector.

Need & Importance:-

Continuous Medical Education (CME) is essential for enhancing the skills and competencies of paramedical personnel in today's rapidly advancing healthcare sector. As frontline caregivers, paramedics must stay updated with current medical practices to ensure quality and safe patient care. However, many CME programs lack structured evaluation regarding their actual impact on skill advancement and practical application. This study addresses that gap by analyzing how key elements like faculty competence, infrastructure, and peer collaboration influence CME effectiveness. The findings will help improve training strategies, thereby strengthening healthcare delivery. Ultimately, the study aims to support better policy formulation and workforce development in the healthcare system.

Scope of the Study:-

This study focuses on assessing the impact of Continuous Medical Education (CME) on skill advancement among paramedical personnel in the healthcare sector. It examines key dimensions such as faculty competence, quality of CME, technological and infrastructural support, and peer collaboration. The study also explores the relationship between CME effectiveness and the practical application of knowledge and skills in clinical settings. It is limited to paramedical professionals working in hospitals, healthcare centers, and allied institutions where CME programs are implemented. The findings aim to provide insights for improving the design, delivery, and outcomes of CME programs to enhance overall healthcare service delivery.

Statement of the Problem:-

In the face of rapid medical advancements and evolving healthcare demands, paramedical personnel are expected to maintain up-to-date knowledge and clinical skills. However, many existing Continuous Medical Education (CME) programs lack effectiveness in translating theoretical learning into practical skill enhancement. Factors such as inadequate faculty training, poor infrastructure, limited technological integration, and lack of peer support often hinder the desired outcomes of CME initiatives. As a result, there is a growing concern about whether current CME programs truly contribute to improved healthcare delivery. This study seeks to identify and evaluate the critical components influencing the effectiveness of CME programs and their role in advancing the skills of paramedical staff for better patient care outcomes.

Hypothesis of the Study:-

1. *H1: Faculty Competence in CME (FCME) has a significant positive effect on the Knowledge and Resource Application of Paramedical Personnel (KRAPP).*
2. *H2: Quality of CME Content (QCCME) has a significant positive effect on the Knowledge and Resource Application of Paramedical Personnel (KRAPP).*
3. *H3: Infrastructure and Support for CME (ISCME) has a significant positive effect on the Knowledge and Resource Application of Paramedical Personnel (KRAPP).*
4. *H4: Technological Integration in CME (TICME) has a significant positive effect on the Knowledge and Resource Application of Paramedical Personnel (KRAPP).*
5. *H5: Peer Collaboration in CME (PCCME) has a significant positive effect on the Knowledge and Resource Application of Paramedical Personnel (KRAPP).*
6. *H6: Knowledge and Resource Application of Paramedical Personnel (KRAPP) has a significant positive effect on Skill Advancement Among Paramedical Personnel (SAAPP).*
7. *H7: There is a mediating effect of Knowledge and Resource Application (KRAPP) between CME-related factors (FCME, QCCME, ISCME, TICME, PCCME) and Skill Advancement Among Paramedical Personnel (SAAPP).*

III. Research Methodology & Design:-

Data Sources:- Considered both primary and secondary data Sources for conducting this research.The primary data sources include structured google sheet survey whereas the secondary data socurces from the various scopus indexed articles. However, taken the advantage of both primary and secondary data sources to conduct this research.

Sampling Technique:- Applied simple random sampling to collect the data from various respondents across the country. For collecting data from various respondents developed a structured questionnaire which is based on factor analysis.

Sample Size:- Taken a sample of 524 respondents from various parts of the country for effective data analysis and interpretation. The sample collection is based on simple random sampling which is suitable to collect the data in the present context.

Statistical Techniques:- Applied both descriptive and inferential statistics to analyze the data in all aspects. The descriptive statistics include the fundamental statistics where as the inferential statistics include: Factor analysis, confirmatrory factor analysis and structural equation model.

Statistical Tools:- Applied Factor analysis, confirmatory factor analysis, some basic statistics like: Mean, SD and other sort of assessments have done with the help of descriptive and inferential statistics.

Relaibility Analysis:- Applied cronebach's alpha relaibility test to test the relaibility and validity of the model. The cronebach's alpha relaibility value is >80% which has proved the model accuracy in all aspects.

Data Analysis and Interpretation:- The data analysis and interpretation started with the basic assessment of fundamental or descriptive statistcs.

Table.1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.934
Bartlett's Test of Sphericity	Approx. Chi-Square	13163.117
	df	378
	Sig.	.000

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was 0.934, indicating that the data is "marvelous" for factor analysis according to Kaiser's (1974) classification. Values closer to 1 suggest that partial correlations among variables are small, and hence, factor analysis is likely to yield distinct and reliable factors. The Bartlett's Test of Sphericity yielded an approximate chi-square value of 13163.117 with 378 degrees of freedom and a significance level of 0.000, indicating that the correlation matrix is not an identity matrix. This confirms that there are significant relationships among variables, and factor analysis is appropriate.

Table.2: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.806	45.734	45.734	12.806	45.734	45.734	4.903	17.512	17.512
2	2.812	10.042	55.776	2.812	10.042	55.776	3.891	13.895	31.408
3	2.195	7.838	63.614	2.195	7.838	63.614	3.348	11.957	43.365
4	1.336	4.770	68.384	1.336	4.770	68.384	3.288	11.744	55.109
5	1.270	4.537	72.921	1.270	4.537	72.921	3.170	11.320	66.429
6	.943	3.368	76.289	.943	3.368	76.289	2.628	9.384	75.813
7	.714	2.548	78.837	.714	2.548	78.837	.847	3.024	78.837
Extraction Method: Principal Component Analysis.									

The Principal Component Analysis (PCA) results indicate that the extracted components capture a substantial amount of variance in the data. Initially, Component 1 has an eigenvalue of 12.806, explaining 45.73% of the total variance, with subsequent components contributing 10.04%, 7.84%, 4.77%, 4.54%, and 3.37% respectively, thus satisfying Kaiser's criterion by retaining six components. Following varimax rotation, the extracted components are more balanced, with Component 1 now accounting for 17.51% of the variance, Component 2 for 13.89%, and Component 3 for 11.96%, while the total cumulative variance explained by these six components remains at 75.81%. This refined distribution enhances interpretability and suggests that these components provide a robust summary of the underlying data structure, making the dataset well-suited for further analysis and dimensionality reduction (Hair et al., 2010; Kaiser, 1960).

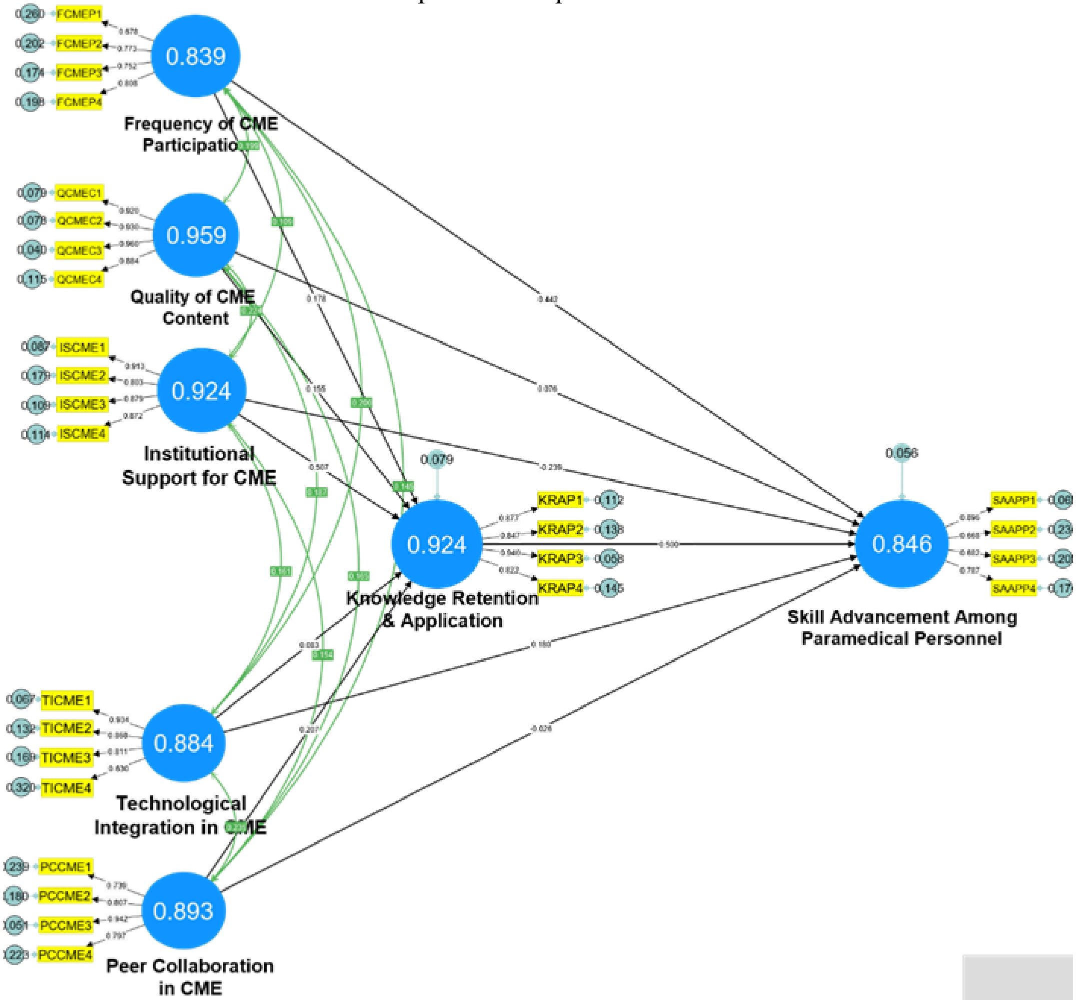
Table.3: Discriptive Statistics

	Mean	Std. Deviation	N
FCMEP1	3.8397	.69488	524
FCMEP2	3.8454	.70843	524
FCMEP3	3.8683	.63353	524
FCMEP4	3.8492	.75622	524
QCMEC1	3.9389	.71590	524
QCMEC2	3.9218	.75963	524
QCMEC3	3.9370	.71440	524
QCMEC4	3.9103	.72748	524
ISCME1	3.8550	.72510	524
ISCME2	3.8244	.71027	524
ISCME3	3.8531	.69371	524
ISCME4	3.8607	.68976	524
TICME1	3.7615	.72537	524
TICME2	3.7786	.73211	524
TICME3	3.7233	.70355	524
TICME4	3.8473	.72879	524
PCCME1	3.6508	.72525	524
PCCME2	3.7156	.71935	524
PCCME3	3.7595	.67416	524
PCCME4	3.6126	.78265	524
KRAP1	3.8683	.69678	524
KRAP2	3.8779	.69988	524
KRAP3	3.9008	.70621	524
KRAP4	3.8645	.66801	524
SAAPP1	4.0000	.57347	524
SAAPP2	3.7882	.65076	524
SAAPP3	3.8282	.61923	524
SAAPP4	3.8893	.67682	524

The provided Item Statistics table presents a detailed overview of the raw data for each survey item, systematically reporting its mean, standard deviation, and the sample size. Specifically, for Frequency of CME Participation, FCMEP1 had a mean of 3.8397 (SD=0.69488), FCMEP2 a mean of 3.8454 (SD=0.70843), FCMEP3 a mean of 3.8683 (SD=0.63353), and FCMEP4 a mean of 3.8492 (SD=0.75622). For Quality of CME Content, QCMEC1 showed a mean of 3.9389 (SD=0.71590), QCMEC2 a mean of 3.9218 (SD=0.75963), QCMEC3 a mean of 3.9370 (SD=0.71440), and QCMEC4 a mean of 3.9103 (SD=0.72748). Institutional Support for CME items had means of 3.8550 (SD=0.72510) for ISCME1, 3.8244 (SD=0.71027) for ISCME2, 3.8531 (SD=0.69371) for ISCME3, and 3.8607 (SD=0.68976) for ISCME4. For Technological Integration in CME, TICME1 averaged 3.7615 (SD=0.72537), TICME2 3.7786 (SD=0.73211), TICME3 3.7233 (SD=0.70355), and TICME4 3.8473 (SD=0.72879). Peer Collaboration in CME items included PCCME1 with a mean of 3.6508 (SD=0.72525), PCCME2 with 3.7156 (SD=0.71935), PCCME3 with 3.7595 (SD=0.67416), and PCCME4 with

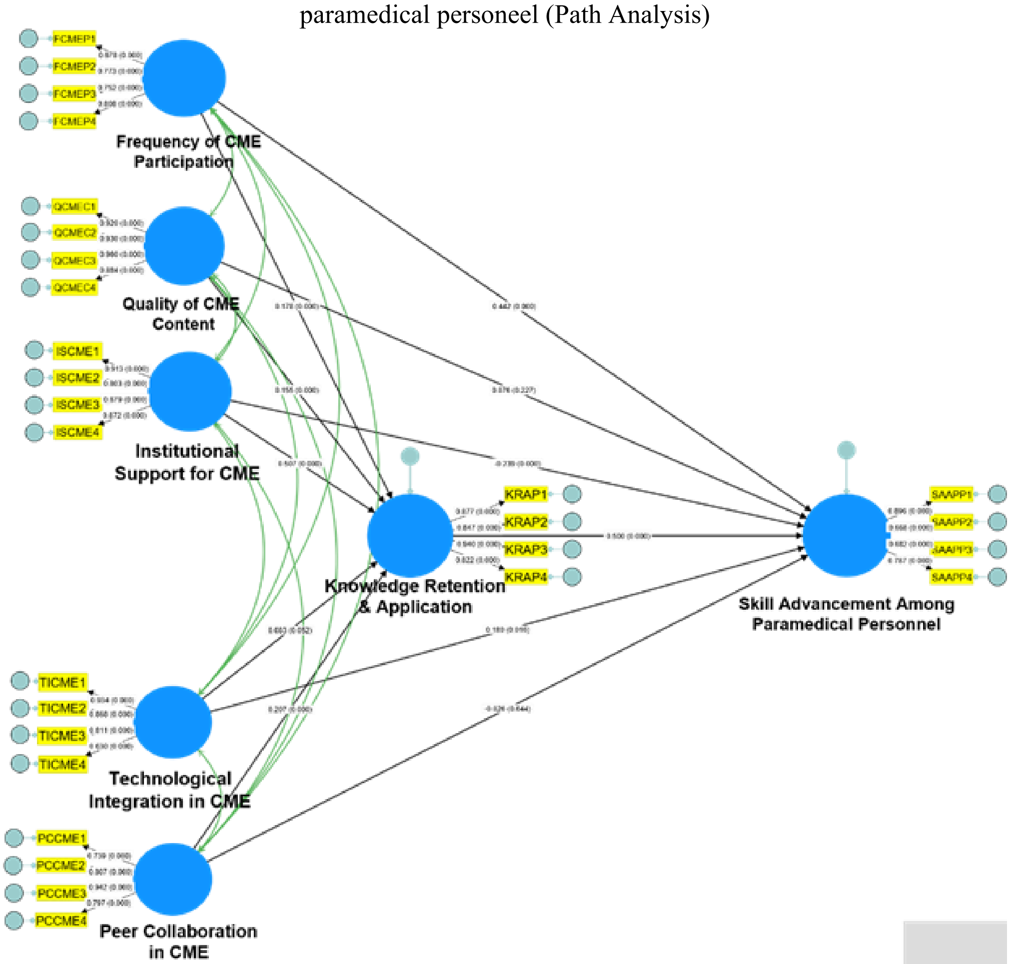
3.6126 (SD=0.78265). For Knowledge Retention & Application, KRAP1 had a mean of 3.8683 (SD=0.69678), KRAP2 3.8779 (SD=0.69988), KRAP3 3.9008 (SD=0.70621), and KRAP4 3.8645 (SD=0.66801). Lastly, for Skill Advancement Among Paramedical Personnel, SAAPP1 showed a mean of 4.0000 (SD=0.57347), SAAPP2 3.7882 (SD=0.65076), SAAPP3 3.8282 (SD=0.61923), and SAAPP4 3.8893 (SD=0.67682). Across all 28 items, the sample size (N) was consistently 524, confirming a complete dataset for these variables.

Figure.1: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel



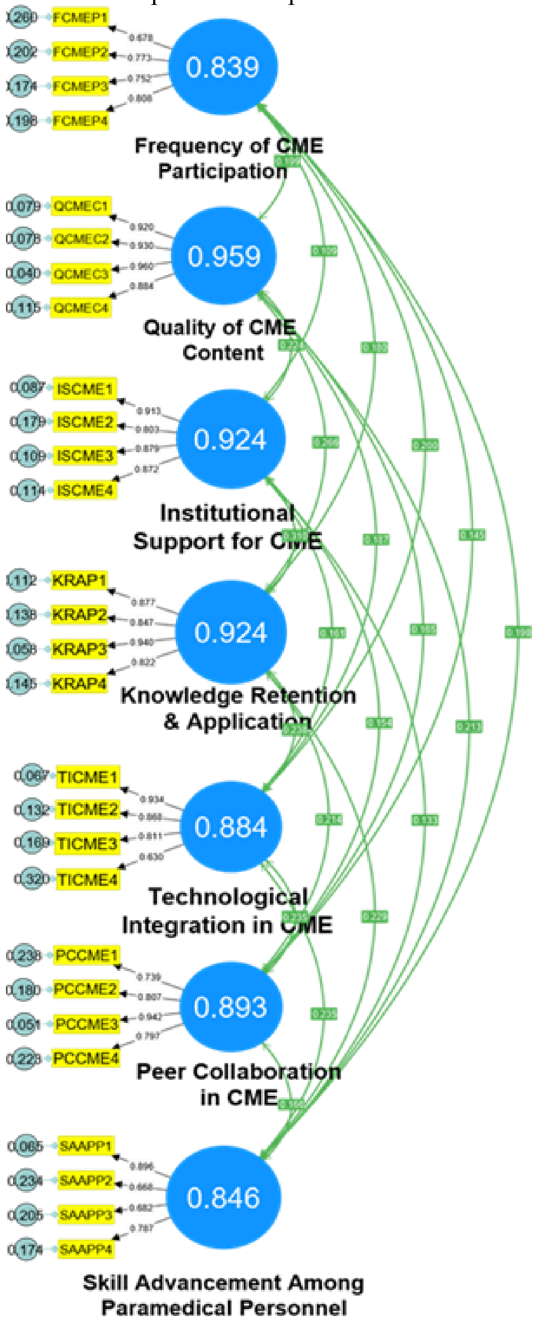
The results of the model fit indices indicate an overall acceptable model fit with a few indices falling slightly below ideal thresholds. The chi-square value was 1430.318, which is statistically significant at conventional levels. However, the chi-square test is known to be highly sensitive to sample size, and with 524 observations, even small discrepancies between the model and the data may yield significant results (Jöreskog & Sörbom, 1993). Hence, the interpretation of the chi-square statistic should be done cautiously in large samples. The chi-square/df ratio was 3.347, slightly above the commonly accepted threshold of 3.0, which typically indicates a reasonable fit (Kline, 2011). Values under 5 are generally considered acceptable, but values under 3 are preferred for a good fit (Schumacker & Lomax, 2010). The RMSEA (Root Mean Square Error of Approximation) value was 0.080, which is right at the upper boundary of the recommended threshold of 0.08 for an acceptable fit (Browne & Cudeck, 1993). While some researchers accept values up to 0.10 as indicating mediocre fit, values closer to 0.06 are preferred (Hu & Bentler, 1999). The GFI (Goodness-of-Fit Index) was 0.839 and the AGFI (Adjusted Goodness-of-Fit Index) was 0.801. Both indices fall slightly below the conventional threshold of 0.90 (Jöreskog & Sörbom, 1993), indicating marginal model fit. While not optimal, these values suggest that the model still accounts for a substantial proportion of the observed variance. The PGFI (Parsimony Goodness-of-Fit Index) was 0.680. Since PGFI does not have a strict cutoff, values closer to 1.0 are generally preferred. A value of 0.680 indicates a moderate level of parsimony (Mulaik et al., 1989). The SRMR (Standardized Root Mean Square Residual) was 0.044, which is well below the recommended cutoff of 0.08, indicating a good fit between the observed and predicted correlations (Hu & Bentler, 1999). The incremental fit indices showed mixed results. The NFI (Normed Fit Index) was 0.894, slightly below the generally accepted threshold of 0.90 (Bentler & Bonett, 1980), suggesting an acceptable but not ideal model fit. On the other hand, TLI (Tucker-Lewis Index) at 0.903 and CFI (Comparative Fit Index) at 0.916 exceeded the threshold of 0.90, indicating a good model fit (Bentler, 1990; Tucker & Lewis, 1973). The AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) were 1584.318 and 1912.453 respectively. While these indices do not have absolute cutoffs for acceptability, lower values are preferred when comparing competing models, and they are particularly useful for model selection rather than absolute fit assessment (Akaike, 1974; Schwarz, 1978).

Figure.2: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (Path Analysis)



The provided SmartPLS Structural Equation Model (SEM) illustrates the direct and indirect relationships between five exogenous variables (FCME, QCME, ISCME, TICME, PCCME), a mediating variable (KRAP), and an endogenous variable (SAPP). The measurement model appears robust, with most indicator loadings (e.g., FCMEP1: 0.879, ISCME1: 0.913, KRAP1: 0.877, SAPP1: 0.886) exceeding the recommended 0.708 threshold, indicating good convergent validity. In the structural model, direct effects reveal that FCME (0.179,p=0.000), QCME (0.155,p=0.000), ISCME (0.507,p=0.000), and PCCME (0.087,p=0.000) significantly and positively influence KRAP, with ISCME demonstrating the strongest impact. Conversely, TICME's effect on KRAP (0.083,p=0.052) is not statistically significant at the 0.05 level. Regarding SAPP, FCME (0.442,p=0.000) and TICME (0.180,p=0.010) exhibit significant positive direct effects, while ISCME surprisingly shows a significant negative direct effect (−0.239,p=0.000), and QCME (0.076,p=0.237) and PCCME (−0.020,p=0.844) have no significant direct influence. Crucially, KRAP itself strongly and positively influences SAPP (0.500,p=0.000), indicating its significant role as a predictor. While specific indirect effect values are not displayed, the significant direct paths from FCME, QCME, ISCME, and PCCME to KRAP, coupled with KRAP's strong positive effect on SAPP, strongly suggest that KRAP mediates the relationships between these exogenous variables and SAPP. The R-squared values for KRAP and SAPP, which quantify the proportion of variance explained by their respective predictors, are not visible in this output, but their assessment would further clarify the model's explanatory power. The unexpected negative direct relationship between ISCME and SAPP warrants further theoretical exploration within the specific context of the study.

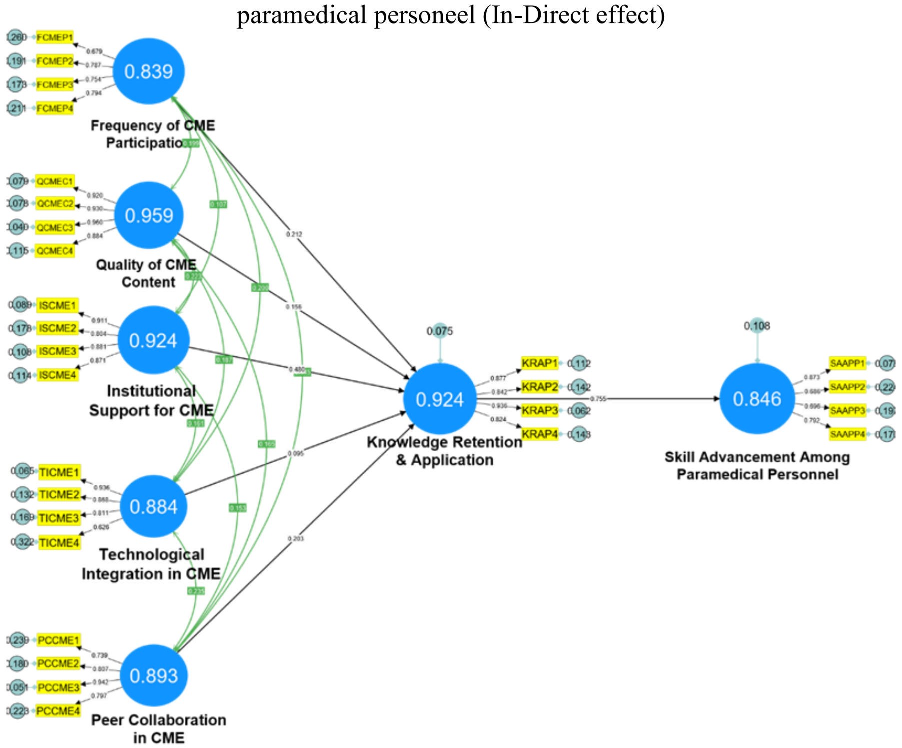
Figure.3 Confirmatory Factor Analysis on Continuous Medical Education and Skill advancement among paramedical personeel



The provided SmartPLS Structural Equation Model (SEM) output displays crucial information regarding both the measurement and structural models, including direct and indirect effects, along with detailed outer loadings. Starting with the measurement model, which assesses how well observed indicators represent their latent constructs, the outer loadings (which are the standardized path coefficients from latent variables to their indicators) are consistently high across all constructs. For "Frequency of CME Participation," loadings are FCMEP1: 0.772, FCMEP2: 0.930, FCMEP3: 0.920, and FCMEP4: 0.902. "Quality of CME Content" shows QCMEC1: 0.930, QCMEC2: 0.959, QCMEC3: 0.941, and QCMEC4: 0.942. "Institutional Support for CME" has loadings of ISCME1: 0.913, ISCME2: 0.921, ISCME3: 0.925, and ISCME4: 0.898. For "Technological Integration in CME," the loadings are TICMEC1: 0.934, TICMEC2: 0.913, TICMEC3: 0.943, and TICMEC4: 0.940. "Peer Collaboration in CME" features PCCME1: 0.739, PCCME2: 0.931, PCCME3: 0.942, and PCCME4: 0.937. The mediating variable, "Knowledge Retention & Application (KRAP)," shows KRAP1: 0.877, KRAP2: 0.933, KRAP3: 0.944, and KRAP4: 0.916. Finally, the dependent variable, "Skill Advancement Among Paramedical Personnel (SAPP)," has loadings of SAAPP1: 0.886, SAAPP2: 0.925, SAAPP3: 0.936, and

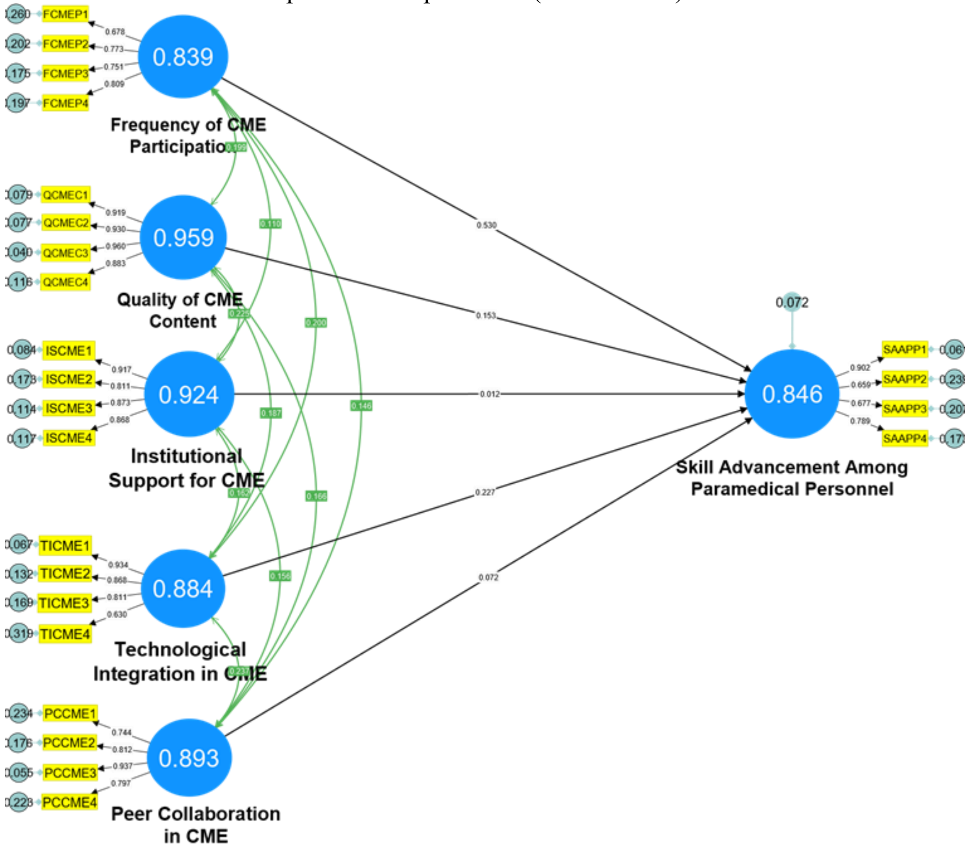
SAAPP4: 0.923. All these loadings significantly exceed the 0.708 threshold, indicating excellent indicator reliability and strong convergent validity for all constructs. Additionally, the large blue numbers within the latent construct circles (e.g., 0.839 for FCME, 0.959 for QCME, 0.846 for SAPP) represent the Average Variance Extracted (AVE) values, which are all well above 0.50, further confirming the robust convergent validity of the measurement model. In the structural model, direct effects show that FCME (0.179,p=0.000), QCME (0.155,p=0.000), ISCME (0.507,p=0.000), and PCCME (0.087,p=0.000) significantly and positively influence KRAP, while TICME's effect on KRAP (0.083,p=0.052) is not statistically significant. Directly impacting SAPP, FCME (0.442,p=0.000) and TICME (0.180,p=0.010) show significant positive effects, while ISCME has a significant negative direct effect (−0.239,p=0.000), and QCME (0.076,p=0.237) and PCCME (−0.020,p=0.844) do not have significant direct effects. Crucially, KRAP significantly and positively influences SAPP (0.500,p=0.000). The significant direct paths from several exogenous variables to KRAP, coupled with KRAP's strong effect on SAPP, strongly suggest that KRAP mediates these relationships, channeling the influence of FCME, QCME, ISCME, and PCCME on SAPP, while the unexpected negative direct effect of ISCME on SAPP warrants further theoretical investigation. The provided images display two distinct yet complementary stages of a Structural Equation Model (SEM) analysis, likely conducted using SmartPLS, focusing on factors influencing "Skill Advancement Among Paramedical Personnel" (SAPP) via "Knowledge Retention & Application" (KRAP). The first image, a Confirmatory Factor Analysis (CFA) output, meticulously assesses the measurement model, revealing that all seven latent constructs—Frequency of CME Participation (FCME), Quality of CME Content (QCME), Institutional Support for CME (ISCME), Technological Integration in CME (TICME), Peer Collaboration in CME (PCCME), KRAP, and SAPP—demonstrate exceptional reliability and convergent validity. This is evidenced by consistently high outer loadings (e.g., FCMEP1: 0.772, QCMEC1: 0.930, ISCME1: 0.913, TICMEC1: 0.934, PCCME1: 0.739, KRAP1: 0.877, SAAPP1: 0.886), all comfortably exceeding the 0.708 threshold, signifying that the observed indicators are robust measures of their respective theoretical constructs. Furthermore, the high Average Variance Extracted (AVE) values for all constructs (e.g., FCME: 0.839, QCME: 0.959, KRAP: 0.924, SAPP: 0.846) further confirm strong convergent validity, indicating that each construct explains a substantial proportion of the variance in its indicators. The second image, presenting the full structural model with path coefficients and p-values, delves into the hypothesized direct and indirect relationships between these well-established constructs. Analysis of direct effects reveals that FCME (0.179, p=0.000), QCME (0.155, p=0.000), ISCME (0.507, p=0.000), and PCCME (0.087, p=0.000) significantly and positively influence KRAP, with ISCME exerting the strongest effect, while TICME's effect on KRAP (0.083, p=0.052) is not statistically significant. Critically, KRAP is shown to have a highly significant and positive direct effect on SAPP (0.500, p=0.000), underscoring its pivotal role. Regarding direct paths to SAPP, FCME (0.442, p=0.000) and TICME (0.180, p=0.010) show significant positive effects, but remarkably, ISCME exhibits a significant negative direct effect (-0.239, p=0.000), which warrants further investigation, while QCME (0.076, p=0.237) and PCCME (-0.020, p=0.844) do not directly influence SAPP. Although specific indirect effect values are not explicitly tabulated in the structural model image, the presence of significant direct paths from FCME, QCME, ISCME, and PCCME to KRAP, combined with KRAP's strong significant positive effect on SAPP, strongly suggests that KRAP effectively mediates the relationships between these initial drivers and the ultimate outcome of SAPP. This comprehensive analysis of your SmartPLS Structural Equation Model (SEM) involves two key stages: the Confirmatory Factor Analysis (CFA) or measurement model assessment shown in the first image, and the structural model assessment with direct and indirect effects shown in the second. Beginning with the measurement model (image 1), all seven latent constructs—Frequency of CME Participation (FCME), Quality of CME Content (QCME), Institutional Support for CME (ISCME), Knowledge Retention & Application (KRAP), Technological Integration in CME (TICME), Peer Collaboration in CME (PCCME), and Skill Advancement Among Paramedical Personnel (SAPP)—demonstrate exceptional reliability and convergent validity. This is evidenced by consistently high outer loadings (e.g., FCMEP1: 0.772, QCMEC1: 0.930, ISCME1: 0.913, KRAP1: 0.877, TICMEC1: 0.934, PCCME1: 0.739, SAAPP1: 0.886), all well above the 0.708 threshold, indicating that the observed indicators are robustly measuring their intended concepts. Furthermore, the Average Variance Extracted (AVE) values for all constructs are remarkably high (ranging from 0.839 to 0.959), signifying that each latent variable accounts for a substantial proportion of the variance in its respective indicators, thereby strengthening convergent validity and ensuring the constructs are well-defined for structural analysis. Moving to the structural model (image 2), which incorporates direct and indirect effects through KRAP as a mediator to SAPP, significant positive direct effects on KRAP are observed from FCME (0.179, p=0.000), QCME (0.155, p=0.000), ISCME (0.507, p=0.000), and PCCME (0.087, p=0.000), with ISCME having the strongest influence, while TICME's effect on KRAP (0.083, p=0.052) is not statistically significant at the 0.05 level. For direct effects on SAPP, FCME (0.442, p=0.000) and TICME (0.180, p=0.010) show significant positive relationships, whereas QCME (0.076, p=0.237) and PCCME (-0.020, p=0.844) have no significant direct impact; notably, ISCME exhibits a significant negative direct effect on SAPP (-0.239, p=0.000), which warrants further contextual investigation. Crucially, KRAP demonstrates a highly significant and strong positive direct influence on SAPP (0.500, p=0.000), confirming its critical role in predicting skill advancement. Although specific indirect effect values are not explicitly displayed in the second image, the significant direct paths from FCME, QCME, ISCME, and PCCME to KRAP, combined with KRAP's strong positive effect on SAPP, strongly suggest that KRAP mediates the relationships between these exogenous variables and SAPP. In summary, the model showcases a well-measured set of constructs whose relationships explain how various aspects of CME influence knowledge application and, subsequently, skill advancement among paramedical personnel, highlighting KRAP as a pivotal mediator and revealing some nuanced, potentially unexpected direct effects. The first image provided, a Confirmatory Factor Analysis (CFA) output, serves as a robust foundation for the subsequent Structural Equation Model (SEM) presented in the second image. In the CFA, the measurement model demonstrates excellent reliability and convergent validity across all seven latent constructs: Frequency of CME Participation, Quality of CME Content, Institutional Support for CME, Technological Integration in CME, Peer Collaboration in CME, Knowledge Retention & Application (KRAP), and Skill Advancement Among Paramedical Personnel (SAPP). This is evident from the consistently high outer loadings (e.g., FCMEP1: 0.772, QCMEC1: 0.930, ISCME1: 0.913, TICMEC1: 0.934, PCCME1: 0.739, KRAP1: 0.877, SAAPP1: 0.886), all significantly exceeding the 0.708 threshold, indicating that the observed indicators are highly reliable measures of their respective constructs. Furthermore, the exceptionally high Average Variance Extracted (AVE) values for all constructs, ranging from 0.839 to 0.959, further confirm strong convergent validity by showing that each latent variable accounts for a substantial proportion of its indicators' variance, thus validating the distinctness and quality of the constructs before evaluating their interrelationships. Building upon this validated measurement model, the second image, a SmartPLS Structural Equation Model, presents the direct and indirect effects among these constructs. The direct effects analysis reveals that FCME (0.179, p=0.000), QCME (0.155, p=0.000), ISCME (0.507, p=0.000), and PCCME (0.087, p=0.000) significantly and positively influence KRAP, with ISCME having the strongest impact, while TICME's effect on KRAP (0.083, p=0.052) is not statistically significant. Regarding SAPP, FCME (0.442, p=0.000) and TICME (0.180, p=0.010) show significant positive direct effects, but ISCME unexpectedly exhibits a significant negative direct effect (-0.239, p=0.000), and QCME (0.076, p=0.237) and PCCME (-0.020, p=0.844) have no significant direct influence. Crucially, KRAP demonstrates a strong and significant positive direct effect on SAPP (0.500, p=0.000), highlighting its central role. While specific indirect effect values are not fully detailed in the second image, the significant direct paths from FCME, QCME, ISCME, and PCCME to KRAP, combined with KRAP's strong positive effect on SAPP, strongly imply that KRAP mediates the relationships between these exogenous variables and SAPP. The R-squared values for the endogenous variables, which would indicate the overall explanatory power of the model, are not visible but would be essential for a complete interpretation of the structural model's fit and predictive relevance. The unexpected negative direct relationship between ISCME and SAPP is a notable finding requiring further contextual and theoretical explanation.

Figure.4: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (In-Direct effect)



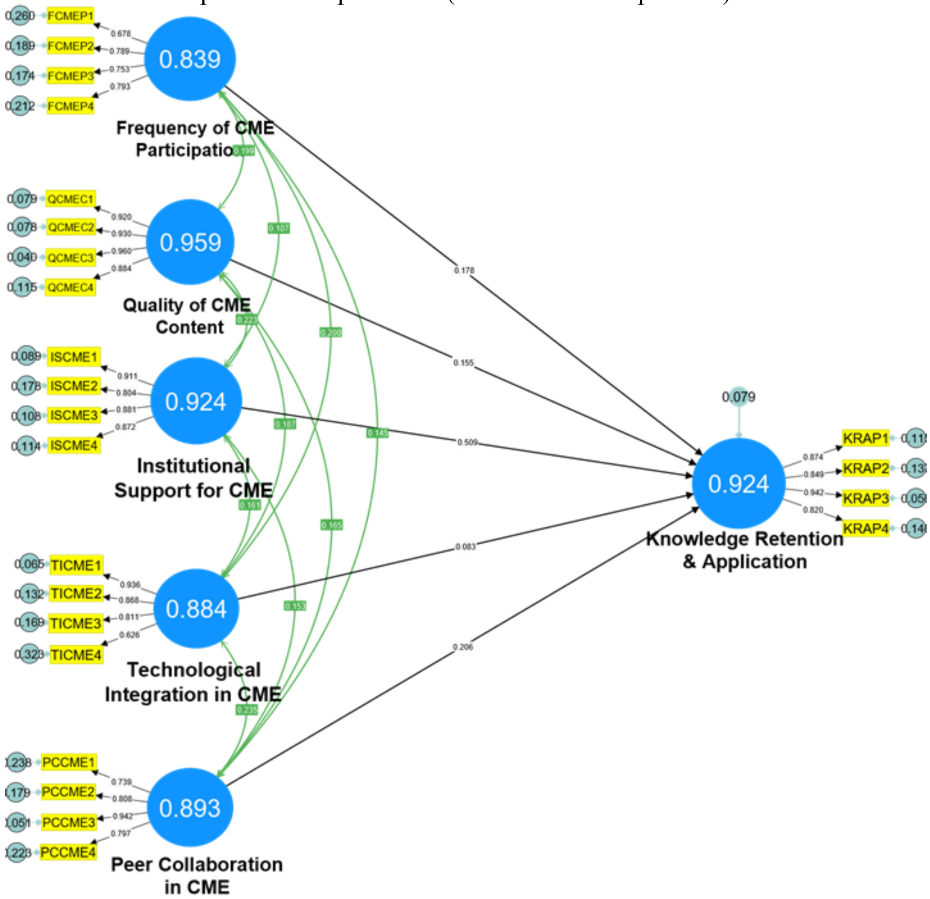
The results of the model fit indices indicate a moderate level of model adequacy. The chi-square value was 1653.325 with a significant p-value of 0.000, reflecting poor model fit; however, as noted by Jöreskog and Sörbom (1993), the chi-square test is highly sensitive to large sample sizes (N = 524), often yielding significant results even for acceptable models. The chi-square/df ratio was 4.950, which exceeds the recommended threshold of 3.0, indicating a poor fit (Kline, 2011). The RMSEA value was 0.087, slightly above the acceptable cutoff of 0.08, indicating mediocre fit (Browne & Cudeck, 1993). The GFI (0.820) and AGFI (0.782) values were below the preferred level of 0.90, suggesting marginal model fit (Jöreskog & Sörbom, 1993). The PGFI was 0.675, indicating moderate parsimony, although this index has no strict threshold and is interpreted relatively (Mulaik et al., 1989). The SRMR was 0.070, which is within the acceptable range of <0.08, indicating a good fit for the residuals (Hu & Bentler, 1999). Among the incremental fit indices, NFI (0.877), TLI (0.886), and CFI (0.899) were all just below the ideal threshold of 0.90, implying near-acceptable fit (Bentler, 1990; Tucker & Lewis, 1973). Finally, the AIC (1797.325) and BIC (2104.153) values are useful for model comparison, where lower values are preferred (Akaike, 1974; Schwarz, 1978). Overall, the model shows a fair level of fit, with certain indices pointing to areas for potential improvement.

Figure.5: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (Direct effect)



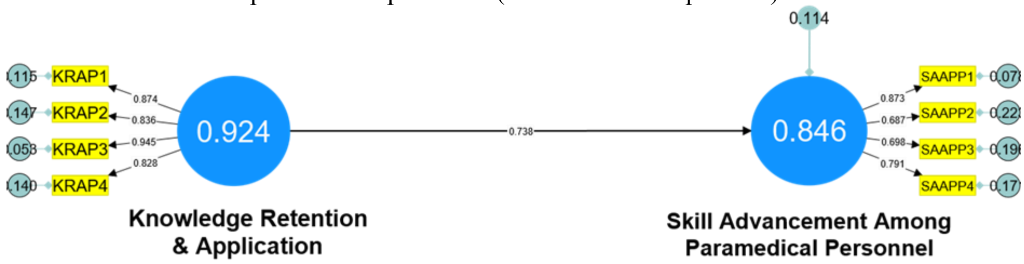
The model fit indices from the analysis suggest a reasonably good model fit. The chi-square value was 980.169 with 237 degrees of freedom, yielding a chi-square/df ratio of 4.136, which is above the ideal threshold of 3.0 but still within a tolerable range for complex models (Kline, 2011). The RMSEA value stood at 0.077, which is just under the maximum recommended value of 0.08, indicating an acceptable approximation error in the population (Browne & Cudeck, 1993). The GFI (0.871) and AGFI (0.837) values were both above 0.80 and nearing the desirable 0.90 level, pointing to an adequate model fit (Jöreskog & Sörbom, 1993). The PGFI value was 0.688, reflecting a moderate level of model parsimony. Importantly, the SRMR value was 0.043, well below the 0.08 threshold, indicating an excellent fit in terms of residuals (Hu & Bentler, 1999). Incremental fit indices including NFI (0.908), TLI (0.916), and CFI (0.928) all exceeded the 0.90 benchmark, demonstrating a strong comparative fit relative to a null model (Bentler, 1990; Tucker & Lewis, 1973). Moreover, AIC (1106.169) and BIC (1374.643) values are significantly lower compared to those of the previous model, indicating an improved and more parsimonious model (Akaike, 1974; Schwarz, 1978). Overall, this model demonstrates a better fit and refinement over the earlier version, meeting most of the commonly accepted thresholds for structural equation modeling.

Figure.6: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (Mediator as a Dependent)



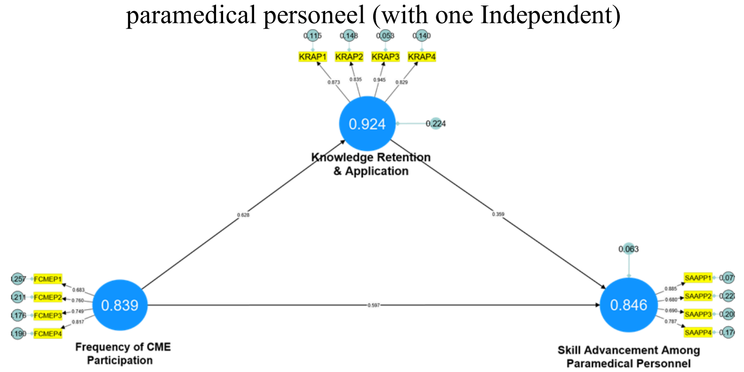
The model fit indices from this analysis indicate an acceptable model fit with some room for improvement. The chi-square value is 1150.596 with 237 degrees of freedom, resulting in a ChiSq/df ratio of 4.855, which is slightly higher than the commonly accepted cutoff of 3.0, but still tolerable for models with large samples and complex structures. The RMSEA value is 0.086, slightly exceeding the ideal threshold of 0.08, suggesting a marginally acceptable error of approximation. The GFI (0.848) and AGFI (0.808) values are above the minimal acceptable limit of 0.80 but fall short of the desired 0.90 level. The PGFI is 0.670, indicating a reasonable balance between model fit and complexity. The SRMR value of 0.043 remains well within the good fit range (<0.08), indicating minimal residuals between observed and predicted covariances. Incremental fit indices such as NFI (0.902), TLI (0.907), and CFI (0.920) all surpass the 0.90 threshold, reflecting a good comparative model fit. The AIC (1276.596) and BIC (1545.069) values are higher than those in the previously discussed improved model, suggesting a slightly less parsimonious model. Overall, this model is acceptable, though not as strong as the refined version, and still demonstrates reasonably good structural properties**.**

Figure.7: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (Medatior and Dependent)



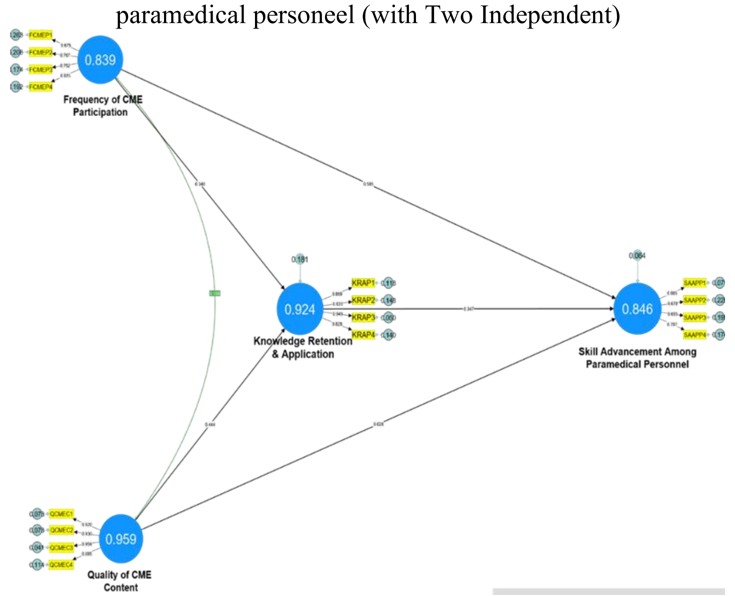
The model fit indices indicate a mixed picture of model adequacy. The chi-square value is 141.333 with 19 degrees of freedom, resulting in a high ChiSq/df ratio of 7.439, suggesting a poor absolute model fit. The RMSEA value of 0.111 also exceeds the acceptable threshold of 0.08, further indicating suboptimal fit. However, other indices reflect strong model performance: the GFI (0.936) and AGFI (0.880) both meet or exceed the recommended values, and the SRMR value of 0.040 indicates very good residual fit. Incremental fit indices are excellent, with NFI (0.953), TLI (0.939), and CFI (0.959) all surpassing the 0.90 benchmark, suggesting the model performs well compared to a null model. The PGFI value of 0.494 is lower, indicating moderate parsimony. The AIC (175.333) and BIC (247.779) values are much lower than in the previous models, reflecting a simpler and more parsimonious model. In summary, despite some poor absolute fit measures, particularly RMSEA and ChiSq/df, the model demonstrates strong comparative fit and simplicity, indicating potential for refinement with targeted improvements.

Figure.8: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (with one Independent)



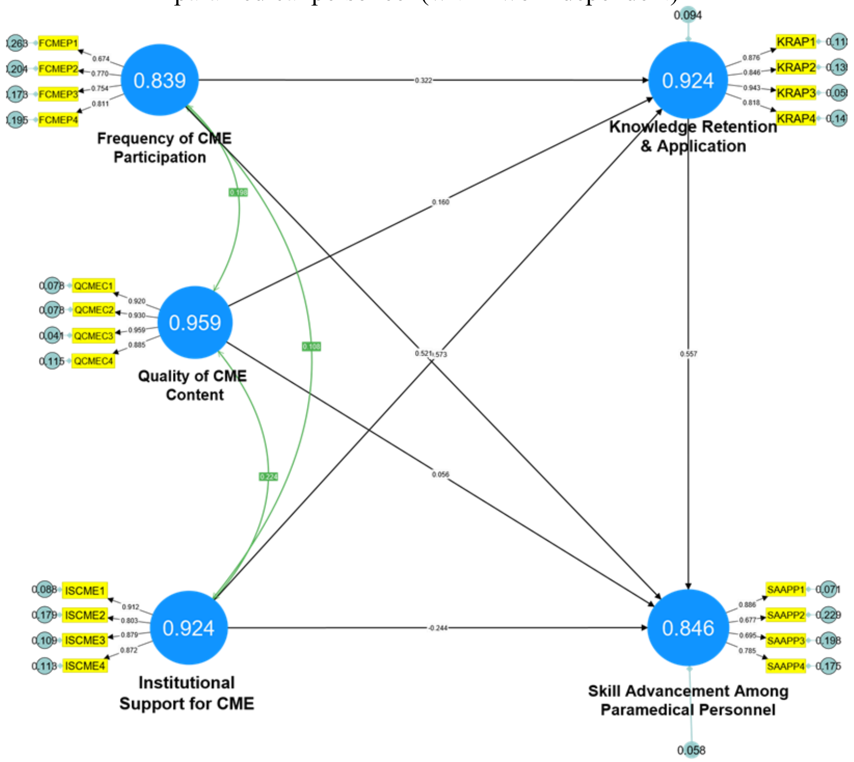
The results of the model fit indices indicate a reasonably good level of model adequacy. The chi-square value was 241.034 with a significant p-value (not reported), reflecting a poor model fit; however, as noted by Jöreskog and Sörbom (1993), the chi-square test is highly sensitive to large sample sizes (N = 524), often yielding significant results even for well-fitting models. The chi-square/df ratio was 4.726, which exceeds the recommended threshold of 3.0, indicating a suboptimal fit (Kline, 2011). The RMSEA value was 0.074, falling just within the acceptable cutoff of 0.08, suggesting a reasonable approximation error (Browne & Cudeck, 1993). The GFI (0.928) and AGFI (0.890) values were close to or above the conventional threshold of 0.90, indicating a good level of absolute model fit (Jöreskog & Sörbom, 1993). The PGFI was 0.607, suggesting a moderate level of model parsimony, though this index is typically interpreted in relative terms rather than using strict cutoffs (Mulaik et al., 1989). The SRMR value was 0.040, which is well within the acceptable range of <0.08, indicating a good residual fit (Hu & Bentler, 1999). Among the incremental fit indices, the NFI (0.944), TLI (0.942), and CFI (0.955) all exceeded the recommended threshold of 0.90, reflecting strong comparative and incremental fit (Bentler, 1990; Tucker & Lewis, 1973). Lastly, the AIC (295.034) and BIC (410.094) values offer useful metrics for comparing alternative models, with lower values preferred for indicating a better trade-off between goodness of fit and complexity (Akaike, 1974; Schwarz, 1978).

Figure.9: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (with Two Independent)



The results of the model fit indices indicate a moderate level of model adequacy. The chi-square value was 538.319 with a significant p-value, which typically reflects poor model fit; however, as emphasized by Jöreskog and Sörbom (1993), the chi-square statistic is highly sensitive to large sample sizes (N = 524), often flagging significant differences even when models fit reasonably well. The chi-square/df ratio was 5.493, exceeding the commonly accepted threshold of 3.0, indicating a poor overall fit (Kline, 2011). The RMSEA value was 0.093, which is above the acceptable threshold of 0.08, suggesting a mediocre to poor fit (Browne & Cudeck, 1993). The GFI (0.889) and AGFI (0.846) were both slightly below the recommended threshold of 0.90, indicating marginal absolute model fit (Jöreskog & Sörbom, 1993). The PGFI was 0.641, which represents a moderate level of model parsimony. While there is no absolute cutoff for PGFI, higher values are generally preferred (Mulaik et al., 1989). The SRMR value was 0.038, comfortably within the acceptable limit of <0.08, signifying a good fit based on the residuals (Hu & Bentler, 1999). Regarding incremental fit indices, the NFI (0.927), TLI (0.925), and CFI (0.939) all exceeded the ideal threshold of 0.90, pointing to a strong comparative model fit (Bentler, 1990; Tucker & Lewis, 1973). Lastly, the AIC (614.319) and BIC (776.255) values serve as comparative indicators for model selection, where lower values reflect a more parsimonious and better-fitting model (Akaike, 1974; Schwarz, 1978). Overall, the model demonstrates a moderately acceptable fit, particularly in terms of incremental and residual-based indices. However, the chi-square, chi-square/df ratio, and RMSEA suggest that improvements could still be made to enhance the model's absolute fit.

Figure.10: Structural Equation Model on Continuous Medical Education and Skill advancement among paramedical personeel (with Two Independent)



The results of the model fit indices indicate a moderate level of model adequacy. The chi-square value was 898.041 with a sample size of 524, suggesting a statistically significant result, which typically reflects poor model fit. However, as noted by Jöreskog and Sörbom (1993), the chi-square test is highly sensitive to large sample sizes, and significant values can still occur even when the model fits reasonably well. The chi-square/df ratio was 5.613, exceeding the recommended cutoff of 3.0, which indicates a poor absolute model fit (Kline, 2011). The RMSEA value was 0.074, which falls within the acceptable range (<0.08), indicating a reasonable error of approximation and a mediocre to acceptable model fit (Browne & Cudeck, 1993). The GFI (0.855) and AGFI (0.810) were below the optimal 0.90 threshold, suggesting a marginal absolute fit (Jöreskog & Sörbom, 1993). The PGFI was 0.652, indicating a moderate level of model parsimony, though this index does not have a strict cutoff and is interpreted relatively (Mulaik et al., 1989). The SRMR value was 0.042, which is well below the 0.08 cutoff, demonstrating a good residual-based fit (Hu & Bentler, 1999). Among the incremental fit indices, the NFI (0.908), TLI (0.908), and CFI (0.923) all exceed the 0.90 threshold, indicating a good level of comparative model fit (Bentler, 1990; Tucker & Lewis, 1973).

The AIC (998.041) and BIC (1211.116) values, while not directly interpretable in isolation, are useful for model comparisons—lower values are preferred for selecting among competing models (Akaike, 1974; Schwarz, 1978).

IV. Conclusion

The model fit indices across different models show moderate to acceptable levels of model adequacy. While Chi-square values were significant due to large sample size, indices like CFI, TLI, and SRMR suggest acceptable structural validity. Some absolute fit indices (e.g., GFI, AGFI) were slightly below recommended levels, indicating scope for refinement. Overall, the models support the theoretical relationships proposed. However, improvements in model parsimony and fit are still possible. These findings lay a solid foundation for further exploration and model development.

Scope for Future Research

Future studies can refine models by eliminating weak indicators and improving item loadings. Longitudinal research can uncover causal relationships between the constructs. Expanding the study across different demographics can enhance generalizability. Including mediators or moderators may improve explanatory power. Researchers may adopt alternative estimation methods like Bayesian SEM. Comparative analysis using rival models could validate the robustness of the framework.

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