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Validation of Instruments for the Improvement of Interprofessional Education through Educational Management: An Internet of Things (IoT)-Based Machine Learning Approach

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Abstract: Educational management is the combination of human and material resources that supervises, plans, and responsibly executes an educational system with outcomes and consequences. However, when seeking improvements in interprofessional education and collaborative practice through the management of health professions, educational modules face significant obstacles and challenges. The primary goal of this study was to analyse data collected from discussion sessions and feedback from respondents concerning interprofessional education (IPE) management modules. Thus, this study used an explanatory and descriptive design to obtain responses from the selected group via a self-administered questionnaire and semi-structured interviews, and the results were limited to averages, i.e., frequency distributions and summary statistics. The results of this study reflect the positive responses from both subgroups and strongly support the further implementation of IPE in various aspects and continuing to improve and develop it. Four different artificial intelligence (AI) techniques were used to model interprofessional education improvement through educational management, using 20 questions from the questionnaire as the variables (19 input variables and 1 output variable). The modelling performance of the nonlinear and linear models could reliably predict the output in both the calibration and validation phases when considering the four performance metrics. These models were shown to be reliable tools for evaluating and modelling interprofessional education through educational management. Gaussian process regression (GPR) outperformed all the models in both the training and validation stages.

Keywords: interprofessional education; interprofessional collaboration; interprofessional education and collaborative practice; education management; IoT; artificial intelligence

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1. Introduction

The primary reasons for the disintegration and lack of awareness of the existing pattern of healthcare are the inefficiencies of the interventions and the quality of the healthcare.

As a result, the policymakers, senior management, and executives responsible for healthcare systems have issued statements acknowledging the need for transformation projects to replace the traditional educational, academic, and clinical practice in health professions with the Interprofessional Education and Collaborative Practice (IPECP) framework. A critical strategy to unite fragmented health systems is to combine old and new educational models.

Many models and theories underpin and reinforce healthcare and health profession development implementation. These theories and models are used in program planning to understand the motivations for health behaviour and to clarify and manage the recognition, growth, and implementation of interventions. However, when identifying a theory or model to guide health, health system advancement, or disease-controlling programs, several factors need to be considered. The health problem, the population targeted for services, and the circumstances in which the program is being implemented all need to be considered and deliberated.

Healthcare improvement and disease prevention programs usually flow from educational theories or models from one or more health professions. These educational theories and models are considered to be complementary health and integrative medicine, which focus on wellness and are governed by IPE frameworks.

IPE offers opportunities for students and professionals in health professions to acquire skills and put them into practice. Practical experience in other health professions enhances their communication and teamwork skills. Additionally, learners and practitioners develop leadership abilities and mutual respect, which better equips them to operate in groups and environments where cooperation is essential for success. IPE also aims to increase public awareness of healthcare delivery reform; decrease clinical errors; and improve safety, patient outcomes, and the job satisfaction of health professionals.

Health education models and theories can be applied singly or in combination according to the approach that best suits the team (learners, colleagues of learners, and instructors) and the clients (patients and stakeholders). Most IPE frameworks (e.g., WHO and IOM) have adapted to accommodate these models and theories in innovative and flexible ways.

Innovative and continuous learning, implementation via the integrated education of health professionals, and the identification of improved educational approaches all reflect a desire to improve patient care, enhance the value of the health system, and make advances in healthcare for the population. IPE emerged from practical improvements and outcomes in healthcare systems and has been strategically developed and incorporated into regular curricula, research, policies, and normative activities at a global level throughout the last decade.

1.1. Literature Review

1.1.1. IPE and IPECP Definitions and Drivers

The process by which students from two or more professions learn about, from, and with one another is known as interprofessional education (IPE).

In contrast, Interprofessional Education and Collaborative Practice (IPECP) is a model of care that is used to improve health outcomes for patients and clients.

The drivers are the results of solid social exchange. Social exchange is achieved through cooperation, collaboration, and communication. IPE and IPECP aim to improve the quality and safety of patient care through collaboration across different professions involving team and group work.

1.1.2. Background

In 1973, as part of a review of medical education, an Expert Committee of the World Health Organization (WHO) recognized that interprofessional education (IPE) and traditional programs were complementary. As the organization responsible for advancing IPE, the WHO plan announced “Health for All by the Year 2000” [1].

Other international organizations, including the WFME (World Federation of Medical Education) [2] and the OECD (Organization for Economic Cooperation and Development) [3], established initiatives to promote IPE experiences.

1.1.3. Framework of Interprofessional Education

IPE is a framework developed by various scholars, institutions, centres, and global organizations. It is a “call to action” for policymakers and decision makers, educators, healthcare professionals, local leaders, and proponents of global health.

1.1.4. IPC (Interprofessional Practice)

IPC is essential to healthcare quality, equity, justice, and safety. Its absence may present a risk to patient safety. IPC is often mentioned as the reason for adverse patient safety events, errors, and omissions when there are conflicts between healthcare professionals [4].

Interprofessional education, learning, and leadership interventions are essential to improve IPC, which could otherwise be considered a "grey area".

1.1.5. Importance of IPECP and Its Future

IPE and IPECP are crucial to the achievement of mutual respect and trust between healthcare teams and work groups, improvements in understanding professional roles and responsibilities, effective communication, increased job satisfaction, and positive patient outcomes.

According to the principles, competencies, objectives, adaptation, and generalizability of IPECP, the future is considered a strategic asset that plays a role in professional accreditation because it can achieve accommodation and implementation that leads to better patient care outcomes [5,6].

1.1.6. IPECP Development and Core Competencies

Via various frameworks (e.g., the Interprofessional Capability Framework of Curtin University, Australia, 2014), IPECP has been developed by IPE centres and institutions around the globe to accommodate the stated goals and objectives.

Based on the common goal, the IPE core competencies are roles and responsibilities, ethical practice, conflict resolution, communication, collaboration, and teamwork with members of other health professions [7].

1.1.7. Barriers to Implementation of IPE

Barriers to IPE include the fear of diluted professional identity, organizational hierarchy, interprofessional rivalries, lack of mutual respect and role conflict, professional boundary infringements, different patient/client care approaches, and tribal/group stereotypes.

These barriers can be overcome through mutual respect and a shared commitment to improving care, the personalities of team members, role understanding and clarity, perceptions of patient/client care quality, perceptions of collaborative relationships, teamwork, characteristics of collaboration, communication, and professional and personal development.

1.1.8. The Influence of Management and Leadership on Interprofessional Education

Educational management is closely concerned with the pursuit of the agendas of educational organizations in terms of planning, decision making, problem solving, and effective organizational team building. Nonetheless, educational management focuses on funding, resources, financial supplies, budget, and budgetary control to meet the objectives of the educational organization. Therefore, interprofessional education as an educational program conducted by an educational organization is dependent on educational management.

In interprofessional education, management and leadership are complicated and challenged by a lack of understanding of the roles and responsibilities of many professional groups. This lack of understanding may lead to ambiguity and conflicts that have a destructive influence on healthcare systems, patient safety, and the quality of professional development [8]. Consequently, faculty or team leaders, such as deans, teachers, tutors, and clinical instructors, have an opportunity to create an atmosphere that encourages the achievement of IPE goals and to act as role paradigms for learners by creating a positive and supportive environment for these goals. Team leaders need to be able to appreciate and value the contributions of interprofessional members to accomplish their common goals and desired results. They must cooperate, communicate, and interact with the interprofessional care team to build and sustain participation to achieve, emphasize, and enhance the significance of the collaborative practice [9]. However, the mission of the management of a healthcare organization requires the IP team to focus on the attainment of goals and the desired outcomes.

Standardizing and systemizing interprofessional care team leadership is vital for the improvement of interprofessional education programs since both improve outcomes that mainly affect the broad spectrum of the healthcare sector. Therefore, the healthcare leaders of today should be mindful of the current situation regarding healthcare delivery arrangements. Furthermore, they should prepare for the future by enhancing their skills and building their capacity to develop the potential of their fellow leaders and colleagues [10–12].

1.1.9. Psychological Implications of IPE

Psychological safety is generally essential for the efficient operation of healthcare organizations and teams. It was also shown that the best learning and development requires a psychologically safe classroom environment.

This need is even more apparent when students are brought together from various healthcare professions because IPE has the unintended consequence of fostering tribalism and the "us vs. them" mindset. However, one of its main objectives is to foster respect and understanding between participants. Hence, as a result, the focus of IPE must be on addressing complex interpersonal dynamics interwoven with traditional healthcare hierarchy and power disparities. To foster a more cooperative interprofessional environment, ideas relating to psychological safety were purposely incorporated into the IPE exercise, creating a safe space for students to analyse the assumptions that exist across many healthcare professions [13].

1.1.10. Pedagogical Implications of IPE

Research results indicate that interprofessional education (IPE) can enhance the attitudes, knowledge, skills, behaviours, and competencies of students. Historically, IPE has typically been featured in the tertiary education training programs for healthcare professionals. Members of different professions can effectively develop a sense of excellence, empathy, intimacy, and altruism through interprofessional education. These characteristics produce signature pedagogies that resemble deep, surface, and implicit systems [14].

1.1.11. Sustainability and IPE

Sustainability is defined as the adaptability to achieve present and future objectives; IPE acquires sustainability characteristics through its supporting pillars (the six core competency domains). The factors that contribute to IPE success and sustainability are as follows:

1. Government funding (government and professional);
2. HEI funding;
3. Faculty development programs;
4. HEI organizational structures to support the integration of IPE into health professional curricula;
5. Staff ownership and commitment across all disciplines involved in IPE programs [15].

Real-world interprofessional education could help to realize the goal of sustainable healthcare and social services, according to a previous statement by the WHO, which cited interprofessional education and collaboration in the health sector as keys to developing better and more long-lasting health services.

1.1.12. Artificial Intelligence (AI) and the Internet of Things (IoT)

The Internet of things (IoT) and artificial intelligence (AI) are two game-changing technologies that are rapidly merging to build more intelligent and interconnected systems [16–18]. The development and comprehension of intelligent systems are supported by a broad range of ideas [19], methods, and principles that constitute the theoretical framework of artificial intelligence (AI).

An introduction to the main components of the AI theoretical framework is provided next.

Machine learning (ML) comprises supervised learning, which utilizes algorithms that learn from labelled data to make predictions or classify new data [20–22]; and unsupervised learning, which utilizes algorithms to find patterns and structure in data without labelled examples and is often used for clustering or dimensionality reduction. Deep learning is a subfield of ML that uses artificial neural networks with many layers (deep neural networks) to model complex patterns. In addition, optimization techniques, including genetic algorithms and gradient descent, are used to fine-tune AI models. An expert system is another form of AI that uses knowledge from human experts to solve complex problems within specific domains. These rely on rule-based systems and knowledge bases [23–26].

Cognitive modelling is also considered a form of AI that aims to replicate human cognitive processes and understand how humans think, learn, and solve problems. This is focused on ensuring that AI systems align with human values and goals and do not behave unexpectedly or harmfully [27–31].

These components form the theoretical foundation of AI and IoT and are often combined and adapted to address specific AI applications and challenges. The field of AI continues to evolve with ongoing research, and interdisciplinary collaboration is expected, drawing from computer science, education, mathematics, psychology, neuroscience, and ethics, among other disciplines [32].

1.2. Objective and Purpose of the Research

1.2.1. Importance of This Research

Because of a lack of aggregate data, evidence regarding the application of interprofessional education (IPE) to global healthcare is limited. This study operated on a reciprocity basis to close this gap. IPE is a phenomenon that "plays a critical role in mitigating the global health workforce crisis". Through the educational management of these models and reflections on collaboration, coordination, cooperation, communication, and praise, educational models for the health professions will be seen as the drivers of IPE improvement [33].

1.2.2. Problem Statement

How could educational model management and theories in the health professions improve interprofessional collaboration and leadership in an educational context?

1.2.3. Research Objectives

The objective of this research study was to set out foundational arguments in support of the statement that educational model management and theories in the health professions are vital components for the improvement of interprofessional education, collaboration, and leadership, and it aimed to achieve the following goals to address research gaps:

- Bring the delivery of healthcare and education closer together;
- Develop a conceptual framework for calculating the impact of IPE;
- Strengthen the empirical base for IPE;
- Examine satisfaction levels with the components of the model related to leadership and improvement in interprofessional education and relate IPE to changes in collaborative behaviour.

1.2.4. Hypothesis

When transformed educational models (IPE) are applied to train learners for practice collaboration, the satisfaction of learners, academic programs, and the community concerned varies in the literature [34].

This study aimed to respond to the following research issues:

- Is there a gap between the educational management models of the health professions and interprofessional education?
- Does the execution of interprofessional education improve the knowledge of health professional learners and practitioners of their field of concern?

- Can health profession educational management theories and models improve interprofessional education and leadership?

This study assessed the lengthy management conditions upon which IPE programs are based. It also considered how to change the perceptions of students regarding interprofessional teams and interprofessional education. It increased the self-reported effectiveness of team members and revealed their capacity to control chronic illnesses.

2. Materials and Methods

2.1. The Sample

This study involved 98 participants in two parallel groups. The first group comprised 14 medical and health professional administrators (leaders, deans, lecturers, and clinical instructors) from the University of Kyrenia, Northern Cyprus; and the National Health Institute, Sudan. The second group comprised 84 medical and health professional learners, as shown in Figure 1, with 53 from the University of Kyrenia, Northern Cyprus; and 31 from the National University, Sudan.

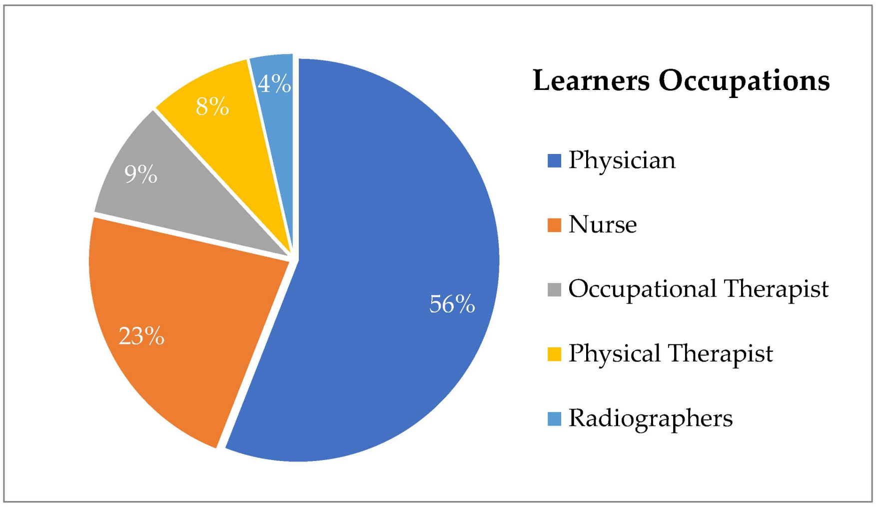

Figure 1. Medical and health professional learners' distribution.

The 84 medical and health professional learners within the age range of 22 to 25 were composed of 57 male candidates and 27 female candidates.

2.2. Design and Model for the Research

An explanatory and descriptive design was used in this research study, which aimed to assess the responses of the selected group via a self-administered questionnaire and semi structured interviews, and the results were limited to averages (i.e., frequency distributions and summary statistics).

The study aimed to measure and to evaluate the educational management models of health professions, outcomes from the improvement of the IPEC module, and the leadership of students. These models were generally assessed at the National Health Institute, Educational Development Centre, Khartoum, Sudan; and the University of Kyrenia, Northern Cyprus.

The assessment focused on medical and health professional learners and clinical instructors.

2.3. Data Gathering and Analysis

The study was managed using a mixed (quantitative and qualitative) approach. The quantitative approach instrument, namely a descriptive method (deductive reasoning), was applied to the 84 medical and health professional learners, and quantitative correlational research (self-administered questionnaires) was applied to the same selected participants.

Furthermore, another qualitative approach method was applied to managerial/administrative group of 14 deans, faculties, tutors, and clinical instructors.

Before applying the aforementioned approaches, Cronbach's alpha was used as a measure of reliability [35].

Then, machine learning approaches were applied, and their performances were evaluated.

2.3.1. Quantitative Approach

In the quantitative approach, paired *t*-tests, the Readiness for Interprofessional Learning Scale (RIPLS), and the Interprofessional Collaborative Competencies Attainment Survey (ICCAS) were used to obtain quantitative data before and after questionnaire completion.

Questionnaires were distributed to the 84 medical and health professional learners in two rounds (pre- and post-test rounds), and orientation sessions were conducted to provide information to all participants.

The Readiness for Interprofessional Learning Scale (RIPLS) and paired *t*-tests were applied to evaluate the pre- and post-questionnaires quantitative data. The results of the RIPLS questionnaire, which consists of 19 attitude questions with four heading measurement items on a 5-point Likert scale, were analyzed as quantitative data (pre and post) for a total of 84 medical and health sciences learner/student participants.

The Interprofessional Collaborative Competencies Attainment Survey (ICCAS) is an instrument for the self-assessment of interprofessional collaborative behaviour, and it is effective when used together with other appraisal instruments to assess the strengths, limitations, and effectiveness of courses. The ICCAS was created to evaluate how the interprofessional collaboration-related competencies of healthcare students and practicing physicians change after IPE training interventions. This 20-item self-report tool assesses the collaboration abilities, conflict management/resolution skills, roles and duties, collaborative patient/family-centred approach of participants, and team functioning.

The participants completed the ICCAS instrument following IPE training but rated their skills twice: first, as they recalled them before training, and again once training was completed. This method is known as a retrospective pre–post approach. The outcomes can assist individuals in reflecting on how training affects their teamwork competencies and allow for IPE intervention programs to assess the efficacy of interventions. According to the validity investigation, high internal consistency and a single explanatory factor were found for all six categories [36].

The hypotheses tested were as follows:

H0: *There is no significant difference between the means of the paired variables.*

H1: *There is a significant difference between the means of the paired variables.*

2.3.2. Qualitative Approach

Qualitative methods using the chi-squared test and open-discussion interviews were applied, respectively, to the 84 medical and health professional learners and to a set of 14 clinical instructors to measure, evaluate, and assess the data outcomes for the goodness of fit to find out how well the sample data fitted the data expected from the population and the independence of the derived results.

The chi-squared test is a nonparametric statistical measure for qualitative data that was used as the goodness-of-fit test and test of independence of all variables in this study.

Based on the conceptual model developed by D'Amour and colleagues, a questionnaire consists of 10 questions to measure interprofessional collaboration between medical and health sciences students was applied [37].

Open-discussion interview questionnaires can be helpful for research, together with a valid measurement, to estimate the degree of collaboration between different professions from different disciplines. The variation in the analysis test results indicated that the instrument had a two-factor structure in which collaboration was recognized as the interpersonal character between professions.

2.3.3. Machine Learning-Based Approaches

The questionnaire was also evaluated and verified using the Internet of things (IoT) in the form of artificial intelligence (AI)-based techniques, namely three different nonlinear models (RT, SVM, and GPR) and a classical linear LR model. Of the 20 questions answered by the respondents, the promotion of effective communication between members of an interprofessional (IP) team (PEC) was considered the output variable, whereas the others were regarded as the input variables.

RT Machine Learning-Based Approaches

A regression tree (RT) is a nonparametric machine learning method and predictive modelling approach that does not require the normalization or scaling of data. This method can be used with many different functional forms [38]. An RT is a supervised learning-based nonlinear model.

Regression tree (RT) algorithms are a subset of decision tree algorithms and are specifically designed for solving regression problems. Unlike classification trees, which are used to predict discrete class labels, regression trees are used to predict continuous numeric values [39]. Like all decision trees, regression trees have a hierarchical, tree-like structure. Each node in the tree represents a decision point based on the value of a feature, and each leaf node represents a prediction for the target variable. The primary goal in building a regression tree is to select the best feature and split point at each node to minimize the error in predicting the continuous target variable. Standard splitting criteria for regression trees include minimizing the mean squared error (MSE), mean absolute error (MAE), or another relevant metric [40]. The tree-building process is recursive, starting from the root node (the entire dataset) and splitting it into subsets at each internal node based on the chosen splitting criteria [41]. This process continues until specific stopping criteria are met, such as a specified tree depth or a minimum number of data points in a leaf node [42]. In regression trees, the prediction at each leaf node is typically a single numeric value, often the mean or median of the target variable for the data points within that leaf node [43].

SVM Machine Learning-Based Approaches

Support vector regression (SVR) is a supervised machine learning technique used for regression tasks [44]. It is a variation of a support vector machine (SVM), which is primarily used for classification tasks. SVR aims to find a hyperplane that best fits the data while minimizing the margin of error between the predicted values and the actual target values [45]. In SVR, the goal is to find a hyperplane that best represents the relationship between the input features and the target variable. Unlike classification, in which the hyperplane separates the classes, regression uses the hyperplane to predict continuous values [46]. SVR can use kernel functions to map the input features into a higher-dimensional space, making it possible to capture more complex relationships in the data. Standard kernel functions include linear, polynomial, radial basis, and sigmoid functions [47].

GPR Machine Learning-Based Approaches

Gaussian process regression (GPR) is a powerful probabilistic machine learning technique for regression tasks. It is based on Gaussian processes, which are flexible and nonparametric approaches to modelling relationships between input features and output values. GPR provides predictions and a measure of uncertainty associated with those predictions, making it valuable for decision making and uncertainty quantification [48]. A Gaussian process is a collection of random variables where any finite subset of these variables follows a joint Gaussian distribution. The Gaussian process models the relationship between input features and output values in GPR. It represents a distribution of functions rather than a single fixed function. GPR provides a predictive mean for each input point, which is the expected value of the output variable given the input features [49–51]. This predictive mean represents the best estimate of the target variable. During training, GPR learns the hyperparameters of the kernel function from the training data. During inference, GPR uses the learned Gaussian process to make predictions and estimate uncertainties for new, unseen data points [52].

Classical Linear Regression Model Machine Learning-Based Approaches

Linear regression (LR) is a fundamental statistical and machine learning technique used for modelling the relationship between a dependent variable (target) and one or more independent variables (features or predictors) [53]. It assumes a linear relationship between the predictors and the target, aiming to find the best-fitting linear equation that describes this relationship. Linear regression is widely used for various applications, including predicting sales based on advertising spending, estimating housing prices, and analysing the impact of independent variables on a dependent variable [54]. It is a foundation for more complex regression techniques and a valuable tool for statistical analysis and machine learning [24,55–57].

3. Results

3.1. Quantitative Approach

3.1.1. Interprofessional Collaborative Competencies Attainment Survey (ICCAS)

The total number (six) of heading items with no missing values pre- and post-ICCAS are shown in Table 1.

Table 1. Frequency summary table for all items.

	Pre-ICCAS	**Post-ICCAS**
Valid	6	6
Missing	0	0

3.1.2. ICCAS and Paired-Samples *T*-Test

Paired samples for pre- and post-ICCAS were divided into six categories. In the pre-ICCAS pair, participant states that: “Before participating in the learning activities I was able to” and in the post-ICCAS the participant declares: “After participating in the learning activities I am able to”:

a. Communication:
    1. Promote effective communication among members of an interprofessional (IP) team.
    2. Actively listen to IP team members’ ideas and concerns.
    3. Express my ideas and concerns without being judgmental.
    4. Provide constructive feedback to IP team members.
    5. Express my ideas and concerns in a clear, concise manner.

b. Collaboration:
    6. Seek out IP team members to address issues.
    7. Work effectively with IP team members to enhance care.
    8. Learn with, from and about IP team members to enhance care.

c. Roles and Responsibilities:
    9. Identify and describe my abilities and contributions to the IP team.
    10. Be accountable for my contributions to the IP team.
    11. Understand the abilities and contributions of IP team members.
    12. Recognize how others’ skills and knowledge complement and overlap with my own.

d. Collaborative Patient/Family-Centred Approach:
   13. Use an IP team approach with the patient to assess the health situation.
   14. Use an IP team approach with the patient to provide whole person care.
   15. Include the patient/family in decision-making.
e. Conflict Management/Resolution:
   16. Actively listen to the perspectives of IP team members.
   17. Take into account the ideas of IP team members.
   18. Address team conflict in a respectful manner.
f. Team Functioning:
   19. Develop an effective care plan with IP team members.
   20. Negotiate responsibilities within overlapping scopes of practice [58].

As shown in Table 2, the paired-samples *t*-test results indicated a mean of 12, a 95% confidence interval of the difference between 7.750 and 16.250. It also showed that the pre- and post-ICCAS results were significantly different, with a p-value < 0.05.

Table 2. Paired-samples *t*-test.

		Paired Differences					*t*-Test	df	Sig. (2-Tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Pre- and post-ICCAS	12.000	4.050	1.653	7.750	16.250	7.258	5	0.001

3.1.3. RIPLS and Paired *T*-Test

As can be seen from Table 3, the post-test mean score was higher; the t-value was acceptable, as it was less than −2; and the significance level was less than 0.01, indicating that there was a significant difference between the means of the paired variables, thus supporting H1.

Table 3. Paired samples test.

Items	Paired Differences					*t*-Test	df	Sig. (2-Tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1 *	−1.143	0.778	0.085	−1.312	−0.974	−13.457	83	0.000
Pair 2 *	−0.940	0.421	0.046	−1.032	−0.849	−20.480	83	0.000
Pair 3 *	−0.774	0.647	0.071	−0.914	−0.633	−10.968	83	0.000
Pair 4 *	−0.917	0.354	0.039	−0.994	−0.840	−23.715	83	0.000
Pair 5 *	−0.857	0.794	0.087	−1.029	−0.685	−9.898	83	0.000
Pair 6 *	−1.167	0.534	0.058	−1.283	−1.051	−20.024	83	0.000
Pair 7 *	−0.786	0.641	0.070	−0.925	−0.647	−11.228	83	0.000
Pair 8 *	−0.786	0.413	0.045	−0.875	−0.696	−17.445	83	0.000
Pair 9 *	−0.631	0.655	0.071	−0.773	−0.489	−8.835	83	0.000
Pair 10 *	−0.369	0.485	0.053	−0.474	−0.264	−6.968	83	0.000
Pair 11 *	−0.345	0.814	0.089	−0.522	−0.169	−3.887	83	0.000
Pair 12 *	−0.679	0.584	0.064	−0.805	−0.552	−10.647	83	0.000
Pair 13 *	−0.655	0.478	0.052	−0.759	−0.551	−12.546	83	0.000
Pair 14 *	−0.536	0.590	0.064	−0.664	−0.408	−8.322	83	0.000

Table 3. *Cont.*

Items	Paired Differences					*t*-Test	df	Sig. (2-Tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 15 *	−0.250	0.805	0.088	−0.425	−0.075	−2.847	83	0.006
Pair 16 *	−0.774	0.499	0.054	−0.882	−0.665	−14.200	83	0.000
Pair 17 *	−0.845	0.814	0.089	−1.022	−0.669	−9.518	83	0.000
Pair 18 *	−0.476	0.526	0.057	−0.590	−0.362	−8.299	83	0.000
Pair 19 *	−0.500	0.591	0.064	−0.628	−0.372	−7.753	83	0.000

* Pairs in this table are (pre) and (post) the following: 1. Learning with other students/professionals. 2. Patients would ultimately benefit if students/professionals worked together. 3. Shared learning with students/professionals to understand clinical problems. 4. Communication skills. 5. Teamwork skills for students/professionals. 6. Shared learning to understand professional limitations. 7. Learning between students/professionals improves working after qualification. 8. Shared learning is thought of positively. 9. Students/professionals respect and trust each other. 10. I do not want to waste time learning with students/professionals. 11. It is not necessary for students/professionals to learn together. 12. Clinical problem solving with students/professionals to learn effectively. 13. Shared learning to communicate with patients and professionals. 14. I would welcome the opportunity to work on small projects with other students/professionals. 15. I would welcome the opportunity to share workshops with other students/professionals. 16. Shared learning and practice to clarify the nature of patients' problems. 17. Shared learning before and after qualification to be a team worker. 18. I am not sure what my professional role will be/is. 19. I must acquire much more knowledge and skills than other students/professionals.

3.2. Qualitative Approach

3.2.1. Open-Discussion Interviews

Open-discussion interview questions were used to reflect on the feedback and improvement of learners according to the post-test results for IPE. Positive answers supported the positive impact on learners, whereas negative responses provided opportunities for sustainable improvement methods and practices for future IPE learners and administrators, as interviewees suggested including the IPE program in the pre-degree syllabus to ensure a better environment in healthcare fields [37].

Figure 2 provides a summary of answers given by 14 administrative participants (leaders, deans, lecturers, clinical instructors, etc.).

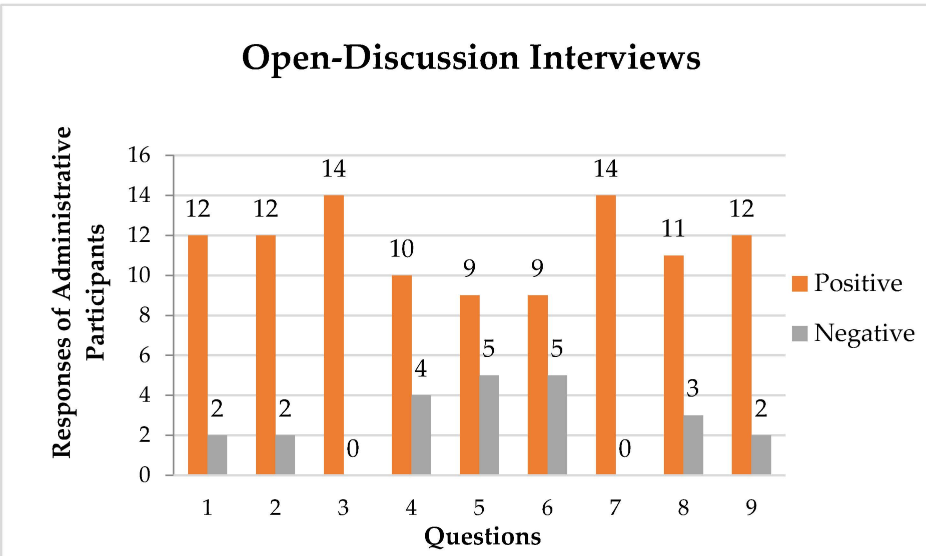

Figure 2. Results of open-discussion interviews.

3.2.2. Chi-Square Test

The chi-squared test is a nonparametric statistical measure for qualitative data and was used as a goodness-of-fit test and test of independence of all 10 variables in this study. These variables were demonstrated the following questionnaire [37]:

1. The existence of explicit shared goals facilitates collaboration and coordination between primary and specialized care. Please rate the current situation in your organization.
2. Explicitly giving priority to the interests and preferences of patients in the interaction between levels of care favours collaboration and coordination between professionals working in the different levels. Please rate the current situation in your organization.
3. Knowledge between professionals of each other's values, specific competences and focus with respect to care, as well as of the environment in which each other work, has an impact on the development of team spirit and collaborative work. Knowing colleagues personally is also helpful. Please rate the current situation in your organization.
4. Mutual trust makes interprofessional collaboration possible, reduces uncertainty and contributes to the formation of networks of multidisciplinary professionals focused on the needs of patients. Please rate the current situation in your organization.
5. The existence of guidelines, issued by the corresponding Health Authority, that promote collaborative work between professionals from different levels of care, influences on the coordination and collaboration between professionals of both care levels. Please rate the current situation in your organization.
6. Shared leadership between managers and clinicians at a local level allows for the development of collaboration between professionals and organizations. Please rate the current situation in your organization.
7. Collaboration requires changes in clinical practice and in the distribution of responsibilities for both primary and specialized care professionals. Such changes require innovation that may or may not be supported by your organization. Please rate the current situation in your organization.
8. For professionals of primary and specialized care to collaborate, they need forums, channels of communication and activities that enable them to come into contact with one another, discuss shared issues and establish links and agreements. Please rate the current situation in your organization.
9. The preparation and establishment of protocols clarifies and makes it possible to negotiate how to share the responsibilities of each professional. Indeed, there are many mechanisms to formalize agreements and understandings between professionals in the two levels: care pathways, information systems, agreements between organizations or units, etc., as well as protocols. Please rate the current use of such mechanisms in your organization.
10. The effective exchange of high-quality information between professionals is an element that facilitates collaboration and makes it possible to provide better care to patients. Please rate the current situation in your organization.

The questionnaire results also show good internal homogeneity between the medical and health science students/learners.

In Table 4, the results show that all items (a–g) had an assumption of 0% cells with expected frequencies of less than five, which was not violated, as it was less than 20%. Shared goals (ShGs), a patient-centred approach (P-CA), mutual knowledge (MK), strategic guidelines (StGs), support for innovation (SI), forums for meetings (FMs), and information systems (ISs), trust, shared leadership (SL), and protocolization had Asymptotic Significance or p-values <0.05. That value was statistically significant, which supported the null hypothesis that items were associated with each other.

Table 4. Chi-square test.

	ShGs	P-C A	MK	Trust	StGs	SL	SI	FMs	Protocol	ISs
Chi-squared	23.073 [a]	58.815 [b]	131.103 [c]	47.741 [d]	106.099 [b]	52.667 [e]	50.533 [f]	48.988 [g]	44.778 [d]	75.605 [b]
df	3	4	4	3	4	3	4	4	3	4
Asymp. Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

[a] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 20.5. [b] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 16.2. [c] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 15.6. [d] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 20.3. [e] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 21.0. [f] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 15.0. [g] 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 16.6.

3.2.3. Cronbach's Alpha

Cronbach's alpha was used as a measure of reliability. It was conducted before applying the different approaches. Table 5 shows that all the Cronbach's alpha coefficients were above 0.7.

Table 5. Reliability statistics.

	Cronbach's Alpha	N of Items
Pre- and Post ICCAS	0.994	2
10 items Questionnaire	0.941	10
RIPLS and Paired *t*-Test pre-variables	0.986	19
RIPLS and Paired *t*-Test post-variables	0.988	19

3.3. Machine Learning-Based Approaches

Based on the correlation analysis described above, it can be understood that PEC had a positive correlation with all the input variables except UAP. Furthermore, it showed a relatively stronger correlation with ALC, SMI, and ACR, with correlation coefficient values equal to 0.6, whereas others had correlations with coefficient values ≤ 0.5, as shown in Table 6. The correlation analysis was conducted to understand the relationship between the variables.

Based on the modelling performance of both the nonlinear and linear models, Table 7 shows that all four models were able to predict the outcome with reliable performance in both the calibration and validation phases by considering the four performance metrics: two fitness indices, namely R-squared (R^2) and Correlation Coefficient (CC); and two error-determining metrics, namely RMSE and MSE. The higher the fitness and lower the error indices, the better the model, and vice versa. Therefore, according to the performance results table, GPR had a higher performance in both the training and validation stages, followed by the LR model. However, GPR outperformed all the other models in both the training and validation stages.

The performance of the models was also visualized graphically, using different illustrations. For instance, a time-series plot was used to identify how well each model predicted the output, as shown in Figure 3.

The performance of the models can also be compared visually, using the scatter plot in Figure 4, which demonstrates the fitness between the predicted results generated from the simulation process and observed values recorded using the questionnaire.

Table 6. Correlation analysis results.

	ALC	EIC	PCF	ECC	SMI	WEE	LWE	IDA	BAC	UAC	RSA	UAA	UAP	IPD	ILP	TAI	ACR	DEP	NRO	PEC
ALC	1.0																			
EIC	0.3	1.0																		
PCF	0.7	0.4	1.0																	
ECC	0.4	0.3	0.6	1.0																
SMI	0.4	0.3	0.6	0.5	1.0															
WEE	0.5	0.6	0.7	0.6	0.4	1.0														
LWE	0.5	0.7	0.7	0.5	0.6	0.8	1.0													
IDA	0.5	0.7	0.6	0.7	0.7	0.6	0.7	1.0												
BAC	0.5	0.6	0.8	0.7	0.6	0.7	0.7	0.7	1.0											
UAC	0.6	0.6	0.7	0.4	0.4	0.5	0.6	0.5	0.6	1.0										
RSA	0.5	0.6	0.5	0.6	0.2	0.6	0.5	0.6	0.6	0.7	1.0									
UAA	0.1	0.5	0.2	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.6	1.0								
UAP	0.1	0.4	0.2	0.5	0.1	0.5	0.3	0.3	0.5	0.4	0.6	0.7	1.0							
IPD	0.6	0.3	0.2	0.3	0.4	0.4	0.4	0.5	0.2	0.4	0.5	0.5	0.5	1.0						
ILP	0.3	0.7	0.4	0.5	0.4	0.6	0.7	0.7	0.6	0.7	0.7	0.8	0.6	0.5	1.0					
TAI	0.2	0.4	0.4	0.5	0.5	0.4	0.5	0.5	0.5	0.5	0.4	0.8	0.6	0.5	0.8	1.0				
ACR	0.7	0.2	0.6	0.3	0.5	0.5	0.4	0.4	0.3	0.6	0.4	0.0	0.1	0.6	0.2	0.2	1.0			
DEP	0.5	0.4	0.5	0.3	0.4	0.6	0.6	0.5	0.3	0.6	0.5	0.4	0.3	0.6	0.7	0.4	0.5	1.0		
NRO	0.3	0.1	0.5	0.5	0.6	0.4	0.4	0.4	0.7	0.4	0.3	0.4	0.5	0.4	0.4	0.7	0.3	0.3	1.0	
PEC	0.6	0.3	0.4	0.4	0.6	0.3	0.4	0.5	0.3	0.4	0.2	0.0	−0.2	0.4	0.2	0.2	0.6	0.3	0.2	1.0

Table 7. Performance of AI models.

	Calibration			
	R^2	**CC**	**RMSE**	**MSE**
RT	0.827	0.909	1.364	1.860
SVM	0.905	0.951	1.010	1.020
GPR	1.000	1.000	0.000	0.000
LR	0.939	0.969	0.810	0.656
	Validation			
RT	0.821	0.906	1.366	1.867
SVM	0.900	0.949	1.062	1.127
GPR	1.000	1.000	0.000	0.000
LR	0.921	0.960	0.857	0.735

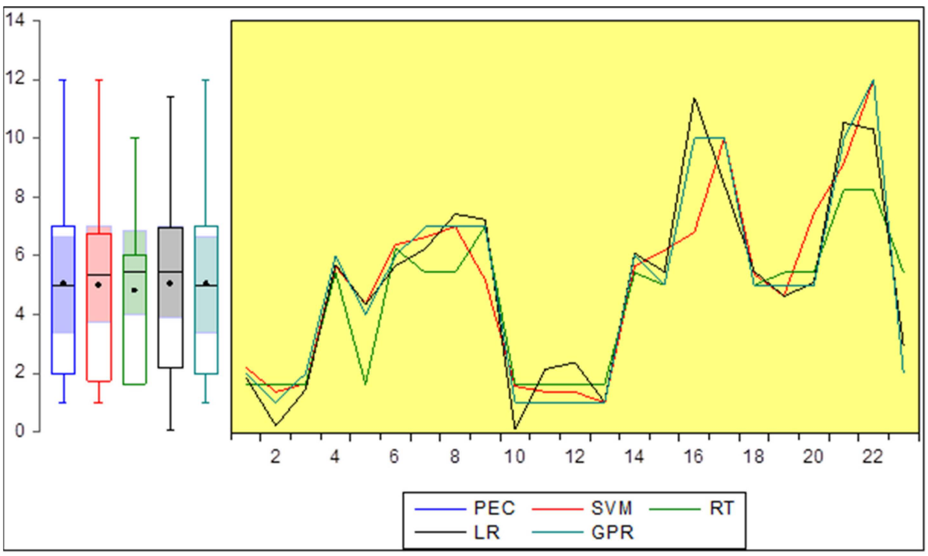

Figure 3. Time-series performance of AI models.

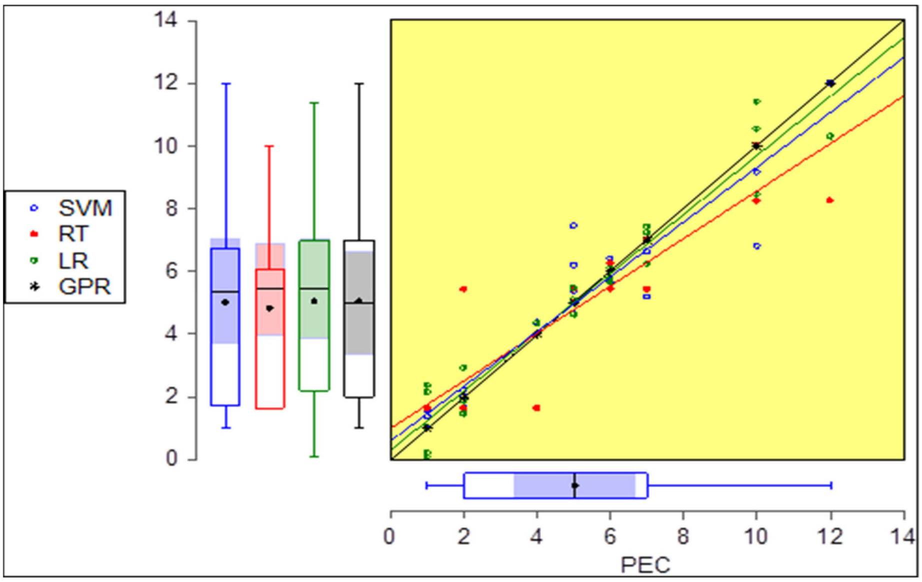

Figure 4. Scatter plot performance of AI models.

The performances of the AI models were also visualized graphically, using the bar chart in Figure 5 to depict the error of each model (MSE and RMSE). The higher the error, the lower the performance of a model is. Therefore, a higher-performance model will demonstrate a lower RMSE and MSE.

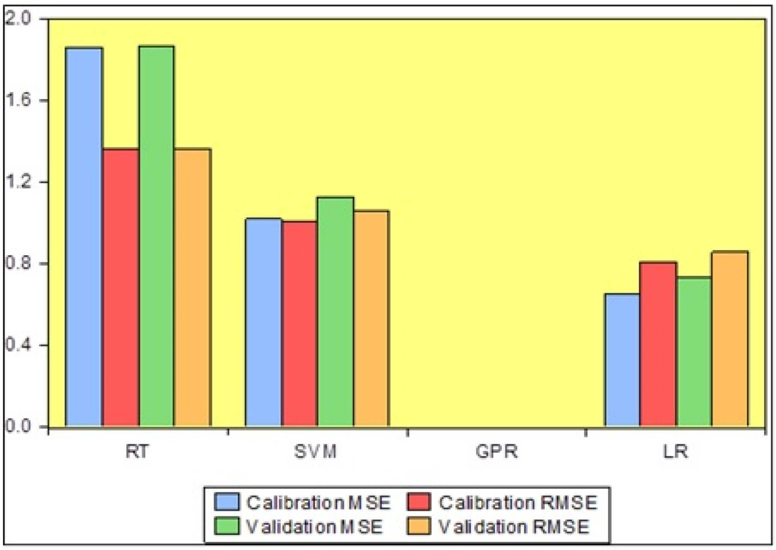

Figure 5. Error demonstrated by AI models.

4. Discussion

Two different methods were applied in the study. The questionnaire of 10 questions and the interview of 9 questions were analysed as qualitative data. The two different methods were analysed regarding two dimensions of collaboration between medical and health sciences students: the first concerned interpersonal relationships between learners, and the second was related to organizational environment characteristics. The interpersonal relationship dimensions indicated the measurement items of shared goals, a patient-centred approach, mutual knowledge, and trust, whereas the organizational features of measurement results related to strategic guidelines, shared leadership, support for innovation, meeting forums, protocolization, and information systems.

Findings

According to the chi-squared test, all ten estimated parameters had a significance value of p-value < 0.05, reflecting the strength of the relationship between the items. The test also showed the goodness-of-fit outcomes for each item. All cells with 0% had an expected count of less than 5. Additionally, the results demonstrate the significant homogeneity and dependability of the questionnaire, and Cronbach's alpha was above 0.90, exceeding the value suggested in [59].

The feedback from the 84 students/learners who responded to the questionnaire demonstrated the positive impact of IPE on the learners. To have a more practical positive impact on IPE, some improvement was needed in trust and shared leadership to achieve greater homogeneity and association with the other measured items.

Interview questions were chosen for the managerial/administrative group of deans, faculties, tutors, and clinical instructors to address the management impact of IPE at the assigned premises. In open-discussion face-to-face interviews in Sudan, nine interview questions were planned. However, because of restrictions associated with the COVID-19 pandemic, which led to the closure and shutdown of all schools, universities, and higher-education institutes in Sudan, alternative, online means were used to conduct interviews. These changes affected the planned interviews and the proposed personal contacts. However, through social media, such as WhatsApp calls, Instagram, and private emails, 14 out of the planned 25 participants were contacted, and their responses and inputs were successfully collected and recorded, despite connectivity problems. Overall, their inputs reflected positive attitudes regarding learner participant impact, management of interprofessional collaboration, and practice programs in rural areas, where self-interactions and communication between medical and health professionals were practiced in a family atmosphere. Some negative feedback (barriers) was offered regarding the lack of supporting materials, shortage of funds and supplies, poor orientation among medical and health professionals, limited numbers of training centres for IPECP, shortsighted plans for healthcare policymakers, and organizational hierarchy in the health structure.

The RIPLS questionnaire was completed by a total of 84 participants, who were medical and health sciences learners/students. It consisted of 19 attitude questions with four heading measurement items on a five-point Likert scale and was analyzed as quantitative data (pre and post) for the study. The four heading items were divided by related attitude questions into teamwork and collaboration, apathetic occupational recognition, constructive occupational recognition, and capacity and influence. The Cronbach's alphas of 0.986 and 0.988 for the pre- and post-questionnaires, respectively, exceeded the 0.7 proposed in [59], thus indicating the reliability and validity of the measurement of IPE using the RIPLS questionnaire for the 84 participants. Furthermore, the overall frequencies show a robust increase in the post-questionnaire results compared with the pre-questionnaire scores, which indicate an improvement in the understanding of IPE by most participants (students/learners).

Paired-samples t-tests were conducted for all 19 attitude questions for the pre- and post-questionnaires. The tests showed a strong positive relationship between two correlated variables (pre and post). A p-value < 0.01 indicated a statistically significant difference wherein the post scores were higher within a 95% confidence interval of the difference in the data results, in which pre was always lower than post; this was acceptable for the study to indicate improvement.

The IPE impact results are consistent with the idea that knowledge of IPE had a positive impact because the 19 RIPLS post-questionnaire attitude question scores were higher than the pre-questionnaire scores, as shown by the paired-samples t-test, indicating clear improvement in IPE understanding among the 84 participants. The questionnaire outcome laid a foundation for future successful collaboration between health professions learners and practitioners.

The ICCAS survey results comprised 20 statements and eight Likert scales to ensure efficient measurement. Between health learners and practitioners (students and graduates), progress was made in communication, collaboration, roles and responsibilities, collaborative patient/family approach, conflict management/resolution, and team functioning; this reflected their expertise in those areas.

In addition, the items in the questionnaire with the highest scores demonstrated the ability of the 84 participants to resolve conflicts and manage responsibilities with appropriate behaviours regarding all items, specifically management/resolution and team functioning.

The R-squared results show that 97.9% of the variance was systematic, which meant that 97.9% of the variance in the post outcomes clarified the pre-outcomes, and the overall model of the ANOVA table was significant. The paired-samples *t*-test was used to research the development of results, as pre was always lower than post when students from two or more different professions learned about, from, and with one another to facilitate effective collaboration and enhance health outcomes [60].

It is recommended that health leaders adopt IPE knowledge and practices to avoid possible outcomes such as organizational pyramids, labels, and tribalism. The involvement of health leaders in improving patient safety and demonstrating a commitment to patient services is based on building a well-established leadership style by recognizing the importance of IPE team management resources and appreciating the efforts of all team members.

The results of the questionnaire, which contained 10 questions with two dimensions that covered interpersonal relationships, were consistent with the literature in measuring shared goals, a patient-centred approach, mutual knowledge, and trust. Organizational characteristics were consistent with the literature in the test of strategic guidelines, shared leadership, support for innovation, meeting forums, protocolization, and information systems. The results of the chi-squared test for the 84 participants show the strength of association between parameters and the goodness of fit to each cell in the test, indicating that there was no gap between the educational management of the health professions and interprofessional education.

5. Conclusions

This study was conducted to identify and fill the gap between health profession management models to improve interprofessional education and leadership in specific locations (the University of Kyrenia, Northern Cyprus; and the National University, Sudan).

The RIPLS questionnaire was utilized to evaluate and measure the changes in the attitudes of learners towards IPE before and after learning and practicing it. High scores in the post-test indicate that IPE were applied successfully. The results also show an improvement in the understanding of teamwork and collaboration between learners from different disciplines, as well as better communication skills and leadership.

This study involved 98 participants divided into three groups. A total number of 14 managerial-level participants were interviewed regarding the feedback of learners on IPE, whereas 84 learners participated in the collection of qualitative data by responding to 10 questionnaire items. The RIPLS questionnaire with 19 attitude questions was completed by 84 participants from different health science disciplines. The study answered the questions mentioned above:

Was there any gap between the educational management models of the health professions and interprofessional education?

There was no gap identified in terms of cooperation and collaboration. This was evident from the evaluation of the 10 questions completed by 84 participants.

Did the execution of an interprofessional education improve knowledge of their field of concern for health professional learners and practitioners?

Yes. The collected data reflected the attitudes of the learners and their enriched knowledge of their professional fields, interprofessional education, and collaborative practice. This was initially visible from the RIPLS results and then emphasized by the ICCAS results that demonstrate improvement in IPE and collaboration between teams.

Could educational management theories and models in the health professions improve interprofessional education and leadership?

The participants (n = 98) all responded positively, and there were no "grey areas". There is an opportunity to embed these theories and models and use them to encourage best practice and goodwill. The reaction and feedback that derived from the collected study information that combined the results of RIPLS, ICCAS, a further 10 questions, and open-discussion interviews showed an acceptable rectification and refinement in leaners' understanding the functions and tasks of the professional health practitioners an positive and constructive feedback from team leaders.

Furthermore, based on the modelling performance of both the nonlinear and linear models, all four models were able to reliably predict outcomes in both the calibration and validation phases in terms of the four performance metrics: the two fitness indices, R^2 and CC; and the error-determining metrics, RMSE and MSE. Nevertheless, GPR outperformed all the models in both the training and validation stages.

The performances of the models are also shown graphically herein, using different illustrations. For instance, a time-series plot is used to identify how well each model predicted the output, as shown in the tables.

In conclusion, these models can serve as reliable tools to model and evaluate interprofessional education management.

6. Recommendations and Future Work

The data were gathered after the study was conducted at Kyrenia University in Northern Cyprus and the National University in Sudan. Consequently, the findings and conclusions cannot be generalized. Therefore, it is recommended that, in a future study, the focus and structure should be expanded to incorporate a larger dataset to enhance its robustness. More tests can be added to the paired t-test and chi-squared test to provide sufficient evidence to answer the research questions.

In addition, the psychological and pedagogical implications should be more thoroughly analysed and discussed in future work.

This will strengthen the foundations for the enhancement of interprofessional education through both educational management and leadership.

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