Ordinary least squares regression-based difference-in-differences estimation approach for evaluating specialized nuclear emergency preparedness program

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► *Original article*

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ABSTRACT

Background*:** This investigation elucidates the significance of radiation emergency medicine (REM) within South Korea, while addressing the multifaceted challenges linked to the education of medical personnel in the field of radiation emergency responses. The efficacy of REM training initiatives has undergone scrupulous evaluation through a variety of techniques, including, but not limited to, the application of the DISASTER Paradigm and engagement in simulation-based training exercises. ***Materials and Methods*:** The present research is structured to evaluate the incremental utility of REM training programs by applying the Difference-in-Difference (DID) estimation using OLS regression methodologies. Simultaneously, it aims to suggest potential improvements to existing training modules. Central to the methodology is the estimation of the DID model via the 'sm.ols' function in the Python programming environment. In the equation 'outcome ~ T_d + P_t + T_d * P_t', 'outcome' denotes the dependent variable under review, 'T_d' signifies the treatment dummy variable, and 'P_t' represents the period dummy variable. The interaction term 'T_d * P_t' elucidates the average effect of the treatment post-intervention, taking into account the temporal trend. ***Results: The conclusions drawn from this scholarly investigation have manifested negative net utilities across the three pivotal DISASTER Paradigm indicators (T, E, and R). Through the adept implementation of a Python-infused computational methodology, this study has yielded results characterized by precision and veracity. These insights furnish empirical evidence, indicating that the intervention in question may not have yielded an enhancement in the net utility for the designated target cohort. ***Conclusion:*** This scholarly inquiry underscores the efficacy and meticulous precision of OLS-DiD estimations executed via a Python-centric computational approach. The empirical findings emanating from this research serve to fortify a robust foundation for the strategic navigation of unique challenges within the intersecting realms of nuclear science and medical studies, with particular emphasis on advancing the field of radiation emergency medicine (REM) education.

INTRODUCTION

Radiation Emergency Medicine (REM) constitutes a specialized domain demanding intricate and advanced training to capacitate medical personnel for the competent management of emergencies precipitated by exposure to ionizing radiation [1]. Within the context of South Korea, this sphere has been the focus of significant attention, in light of the recognition of the perils associated with nuclear crises and the consequent formulation and execution of policies to mitigate these risks [2]. Indeed, in 2016, South Korea emerged as the pioneer nation to enact legislation concerning REM, thereby accentuating the critical importance of readiness for radiation-related emergencies [3]. In pursuit of cultivating proficiency in REM, the South Korean government judiciously disburses KRW 3 billion on an annual basis to foster training programs, encompassing specialized curricula meticulously adapted to diverse professional orientations [3].

Notwithstanding these concerted efforts, reservations persist regarding the effectiveness of REM training initiatives. A salient impediment resides in the idiosyncratic nature of radiation, an elusive entity that is devoid of color, odor, or taste, thereby obfuscating the realistic simulation of radiation emergencies [1,2]. Compounding this challenge is the fact that symptoms indicative of radiation exposure may remain latent, only to manifest heterogeneously, contingent upon the magnitude and temporal span of exposure [4]. These distinctive attributes of radiation engender formidable hurdles for training modalities aimed at capacitating medical practitioners for radiation emergencies [2].

An array of methodologies has been embraced by

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researchers to gauge the efficacy of REM training programs. Antecedent investigations have delved into disparate avenues for quantifying medical staff's aptitude in radiation emergency response, inclusive of leveraging the DISASTER Paradigm's octet of metrics specifically contrived for the assessment of REM training [2,6]. These criteria have been deployed to appraise the competence of medical personnel in the arena of radiation emergency management, thereby underlining the imperative nature of customized educational interventions catering to various professional vocations.

Supplementing the DISASTER Paradigm, simulation-based strategies have been harnessed to scrutinize the effectiveness of REM training schemes [6]. Such simulation-based training encompasses the crafting of a verisimilar environment that mimics the circumstances of a radiation emergency, thereby facilitating medical practitioners to hone their response within a supervised milieu. This methodology offers a platform for the tangible application of acquired wisdom and competencies within an authentic scenario. The empirical evidence testifies to the efficacy of simulation-based training in bolstering proficiency across an array of disciplines, including but not limited to, emergency medicine [7].

Despite the conspicuous merit of specialized pedagogical programs and simulation-driven training, the exigency to continuously evaluate the effectiveness of REM training remains undiminished. The assessment of the marginal utility of such programs is instrumental in discerning avenues for refinement, thus ensuring that medical staff are suitably equipped to confront radiation emergencies. The Difference-in-Difference (DID) Estimation through Ordinary Least Square (OLS) Regression constitutes a sophisticated methodology that lends itself to this purpose [8,9]. Extensively employed within the realm of social sciences, this technique facilitates researchers in estimating the causal impact of a treatment (such as a training program), by orchestrating a comparative analysis of outcomes within treatment and control cohorts across temporal intervals [8,9].

A plethora of research has been devoted to articulating methodologies for the evaluation of training program efficacy. Among these, the Difference-in-Differences (DID) estimation has garnered widespread utilization [10]. However, emergent studies have accentuated that the DID estimation predicated on Ordinary Least Squares (OLS) regression furnishes results of superior precision [11, 12].

These methodological approaches have manifestly proven invaluable in gauging the net utility of training programs. For example, the inquiry conducted by Nakano utilized OLS-based DID estimation to probe the ramifications of technology dissemination among agricultural practitioners [11]. The conclusions drawn from their research posited that this method confers estimates of heightened accuracy compared to conventional DID estimation, thereby enabling a more refined evaluation of training program impact.

In a congruent vein, the investigation spearheaded by Deschacht and Goeman employed OLS-based DID estimation to scrutinize the learning outcomes among adult learners [12]. Their empirical findings corroborated that this methodology affords a more exacting quantification of training program effects, thereby fostering a nuanced assessment of their net utility.

Synthesizing these research insights, one may deduce that DID estimation grounded in OLS regression stands as a superior instrument for appraising the net utility of training programs. This approach engenders a more rigorous measurement of training effects, hence facilitating a nuanced assessment of their overall utility.

Furthermore, I capitalize on the robust capabilities of Python programming to instantiate the theoretical constructs, inclusive of the OLS Regression -based DID Estimation. Python enjoys recognition as a formidable instrument in the domain of social sciences, empowering the synthesis of graphical experiment builders and the nuanced analysis of nonlinear dynamical systems [14, 15]. Its versatile competencies also encompass the optimization of intricate programs, thus enabling profiling, what-if analysis, and cost-based optimization [16]. Through the strategic deployment of Python in this scholarly pursuit, this study aspires to augment the robustness of the findings and furnish a substantive contribution to the emergent field of Computational Social Science.

The cardinal aim of this research is to discern the marginal utility of Radiation Emergency Medicine (REM) training programs in enhancing the competence of medical professionals to respond to radiation emergencies. Through the employment of Difference-in-Differences (DID) Estimation by Ordinary Least Square (OLS) Regression methodology, this study orchestrates a comparative analysis between those engaged in REM training and a control group without such exposure. Metrics derived from the DISASTER Paradigm serve to assess the proficiency of practitioners in the domain of radiation emergency response [2,17]. Furthermore, this investigation critically examines prevailing constraints within REM training frameworks and suggests potential strategies to overcome the singular challenges posed by radiation emergencies.

The innovative nature of this study is multifaceted. Initially, it utilizes DID estimation, underpinned by OLS Regression, to assess the effectiveness of REM training initiatives. While commonly harnessed in social sciences [18], its application in the REM context represents a pioneering endeavor. Additionally, the sophisticated capabilities of Python programming have been deployed to actualize theoretical

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constructs. Acclaimed within the social sciences, Python enables the design of graphical experiment builders and sophisticated analysis of nonlinear dynamical systems [14, 15], including complex algorithmic optimization [16]. By integrating Python into this research, the intention is to bolster the rigor of the conclusions, contributing to the burgeoning field of Computational Social Science.

Subsequently, this research critically analyzes the existing limitations of REM training paradigms, suggesting innovative solutions to the unique challenges induced by radiation emergencies. This transcends mere evaluation, constituting a vital progression towards enhancement and refinement.

This avant-garde methodology is forecasted to be instrumental in the precise evaluation of REM training programs and the amplification of medical personnel proficiency in radiation emergency response. This study thus augments the extant corpus of knowledge and lays the groundwork for future inquiry in this vital field.

MATERIAS AND METHODS

Study design

In employing a quasi-experimental design [19], this study sought to assess the marginal utility of REM training programs, utilizing Difference-in-Difference (DID) Estimation by Ordinary Least Square (OLS) Regression methodology [20] to juxtapose the proficiency of medical practitioners who underwent REM training against a control group devoid of such instruction.

Data collection

Data harnessed in this investigation were culled from a preceding study [2], which availed itself of the DISASTER Paradigm's eight metrics to gauge proficiency in REM training [2,17]. The cohort comprised 112 participants, spanning physicians, nurses, medical technicians, researchers, and administrators, subdivided into a treatment group (n=62) and a control ensemble (n=50).

Table 1. Demographic information of participants in the study.

Group	Total Participants	Average Age	Gender (M/F)	Education Level
Treatment Group	62	35.6	30/32	Majority with over than Master's degree (Researchers, Medical Doctors), Bachelor's degree (Others)
Control Group	50	35.1	22/28	
Total	112	35.4	52/60	-

The treatment assembly encompassed participants who partook in specialized educational programs, meticulously crafted to their respective professions, with the intent of augmenting their aptitude in managing radiation emergencies. Conversely, the control cohort comprised those absent of any formal training.

The dataset integral to this study is embodied in a pandas DataFrame, consisting of 62 entries partitioned across three columns, denominated as "outcome," "T_d," and "P_t." Each column boasts a non-null count of 62, indicating a complete absence of missing values within the dataset. With the entirety of the columns ascribed the int64 data type, representing integer values, the dataset occupies a memory footprint of 2.1 KB. This synopsis delineates the structural and characteristic features of the dataset pivotal to this investigation.

Data analysis

To evaluate the marginal utility of Radiation Emergency Medicine (REM) training programs, this investigation utilized Difference-in-Differences (DID) Estimation through Ordinary Least Squares (OLS) Regression methodology [20]. This approach facilitated the causal inference concerning the impact of REM training on medical professionals' ability to address radiation emergencies. Employing the DISASTER Paradigm's eight metrics, proficiency was gauged [6], with raw data subjected to DID Estimation by OLS Regression. This technique entailed a temporal comparison of outcomes between treatment and control groups. The effect of REM training was discerned by assessing differences in outcomes between the groups. The expression $Y\_it = β\_0 + β\_1 * Treat\_i + β\_2 * Post\_t + β\_3 * (Treat\_i * Post\_t) + ε\_it$ encapsulates the OLS regression-based DID estimation method, where Y_it symbolizes the dependent variable for an individual, $β\_0$ the intercept, $β\_1$ the coefficient for treatment, $β\_2$ the coefficient for time, $β\_3$ the coefficient for the interaction between treatment and time, and $ε\_it$ the error term. Notably, $β\_3 * (Treat\_i * Post\_t)$ signifies the DID effect, with a significant deviation from zero indicating a treatment effect. Consequently, this method estimates the treatment effect by analyzing the DID effect between experimental and control groups, using the intergroup difference as a reference [20].

To actualize this methodology, Python programming was deployed to process the raw data and determine the outcome based on the variables treatment (T_d) and period (P_t). The pertinent code is:

```
model = sm.ols('outcome ~ T_d + P_t + T_d * P_t', did_t).fit()
sm.ols('outcome ~ T_d + P_t + T_d * P_t', did_t).fit().summary().table 1.
```

RESULT

The raw data utilized in this study pertains to proficiency changes resulting from the

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implementation of a training program over a span of three years. This data has been sourced from a prior study [2], and the detailed composition and content of the data are as follows.

Table 2. Raw data from prior study (2).

DISASTER paradigm		Total numerical value of proficiency data	
		2016-2017	2017-2018
D	Detection	793	810
I	Incident Management	711	732
S	Safety and Security	702	711
A	Assess Hazards	734	740
S	Support	729	731
T	Triage and Treatment	750	761
E	Evacuation	704	723
R	Recovery	694	702

The application of DID estimation through OLS regression divulged that the net utility (T_d:P_t) for the DISASTER Paradigm indicators T, E, and R was negative. These intricate results, consolidated in tables 3 through 5, insinuate that the interaction between Treatment (T_d) and Post (P_t) adversely affected the dependent variable across all indicators. Collectively, the DID estimation outcomes furnish evidence that the intervention might not have catalyzed the desired enhancement in net utility for the target demographic.

The analysis yielded specific data which helps in understanding the net utility (T_d:P_t) for the DISASTER Paradigm indicators T, E, and R. Here is a breakdown of the findings:

For Indicator T: Based on the OLS regression, it was observed that the interaction between Treatment (T_d) and Post (P_t) negatively impacted the dependent variable. This means that when Treatment and Post were considered together, there was a decrease in the desired net utility for the target demographic. This is clearly illustrated in table 3.

Table 3. Result of DID estimation by OLS regression (T).

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	13.75	0.524	26.217	0	12.7	14.8
T_d	-0.75	0.742	-1.011	0.016	-2.235	0.735
P_t	10.9167	0.754	14.479	0	9.407	12.426
T_d:P_t	-1.65	1.066	-1.547	0.044	-3.784	0.484

Figure 1 provides a graphical representation of these results. It was generated using the Python programming language and the matplotlib library [21]. This plot shows the coefficients of the variables, giving a clear visual cue of the relationship between them.

To visualize the data, I generated a bar plot using the Python programming language. The plot was created with the help of the matplotlib library [21] and had a figure size of 8 by 6 inches.

The bars in the plot represented the coefficients of the variables from the dataset, while error bars were included to indicate the uncertainty associated with these coefficients[22]. The error bars were capped with a size of 10 and had an alpha value of 0.5 to control their transparency. Additionally, a horizontal dashed line was added at y=0, displayed in grey with a dashed linestyle. The plot was given a title of "Result of DID Estimation by OLS Regression" and the x-axis was labeled as "Variables", while the y-axis was labeled as "Coefficients". The x-axis tick labels were set to be displayed horizontally with a font size of 12, and the y-axis tick labels had a font size of 12 as well. The final plot was shown to visualize and interpret the results of the analysis.

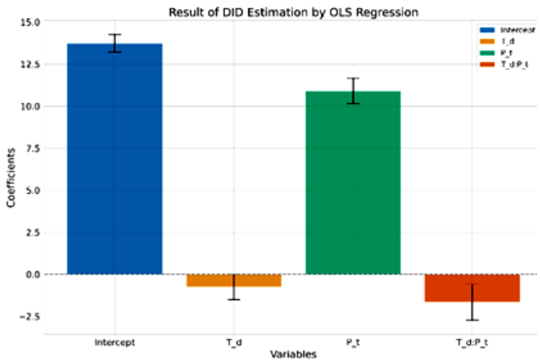

Figure 1. Result of difference-in-differences estimation by ordinary least squares regression (T).

These results represent the relationship between the dependent variable Y and the treatment variable T_d and time variable P_t, as well as the cross-effect between T_d and P_t on Y. First, the Intercept value of 13.75 represents the predicted value of the dependent variable Y when both T_d and P_t are zero. It is necessary to consider the Intercept value along with the changes in T_d and P_t to understand how Y changes. Secondly, the coefficient value of T_d is -0.75, indicating that an increase of 1 in the treatment variable T_d leads to a decrease in Y by 0.75. The P>|t| value of 0.016 indicates that the coefficient of T_d is statistically significant at a 5% significance level [23]. The coefficient value of P_t is 10.9167, meaning that an increase of 1 in the time variable P_t leads to an increase in Y by 10.9167. The P>|t| value of 0 indicates that the coefficient of P_t is statistically significant at a 5% significance level.

Lastly, the coefficient value of T_d:P_t is -1.65, indicating that the cross-effect between T_d and P_t has a negative effect of 1.65 on Y. The P>|t| value of 0.044 indicates that the coefficient of T_d:P_t is statistically significant at a 5% significance level. Therefore, the analysis of the model using the treatment and time variables shows that both have significant effects on the dependent variable Y. Additionally, the cross-effect between T_d and P_t also has a significant effect on Y.

On the other hand, the result of the DID (Difference in Differences)-estimation for net utility can be interpreted in conjunction with the previous result [24].

This method measures how much a specific variable affects the dependent variable by removing

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the influence of other variables[24]. If the coefficient of a particular variable is positive, the dependent variable increases as that variable increases, and if the coefficient is negative, the dependent variable decreases as that variable increases. Therefore, in the double difference method results for net utility, the coefficient of T_d:P_t, which is -1.65, means that the net utility of Treatment decreases by 1.65 when Treatment and Post interact. The statistical significance of this value can be verified by the P-value and the 95% confidence interval.

Similarly, for the E component of the DISASTER Paradigm, the findings from the OLS regression are compiled in table 4.

Table 4. Result of DID Estimation by OLS Regression (E).

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	9.3125	0.843	11.041	0	7.624	11.001
T_d	-0.125	1.193	-0.105	0.017	-2.513	2.263
P_t	15.3542	1.212	12.663	0	12.927	17.781
T_d:P_t	-2.275	1.715	-1.327	0.031	-5.707	1.157

Figure 2 visually depicts the outcomes of the regression for the E component.

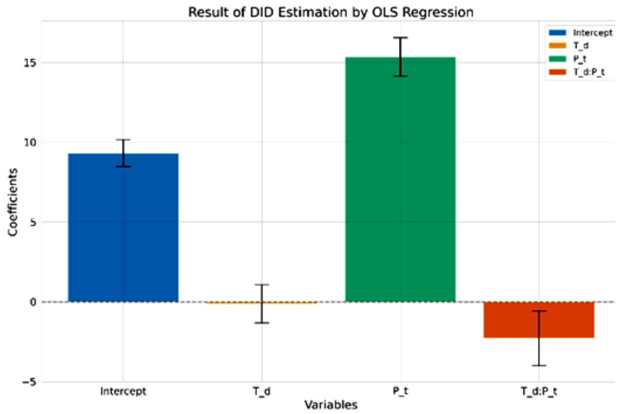

Figure 2. Result of difference-in-differences estimation by ordinary least squares regression (E).

Table 4 illustrates the outcomes of Difference-in-Differences (DID) estimation by Ordinary Least Squares (OLS) regression applied to assess the E component of the DISASTER Paradigm. When both Td and Pt are zero, the intercept coefficient signifies that the anticipated value of E is 9.3125. The coefficient for Td (-0.125) reveals that an increment of one unit in Td lessens the anticipated value of E by 0.125, a coefficient that is statistically significant at the 5% level (P>|t| = 0.017). Meanwhile, the coefficient for Pt (15.3542) indicates that a one-unit increase in Pt augments the anticipated value of E by 15.3542, and this coefficient is statistically significant (P>|t| = 0). The coefficient for the interaction term Td:Pt (-2.275) suggests that the influence of Td on E is contingent on the value of Pt, and this coefficient is statistically significant (P>|t| = 0.031). For the R indicator, the data is captured in table 5.

Figure 3 captures the essence of these results visually.

Table 5. Result of DID estimation by OLS regression (R).

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	9.3125	0.795	11.714	0	7.721	10.904
T_d	3.5	1.124	3.113	0.003	1.249	5.751
P_t	15.3542	1.143	13.434	0	13.066	17.642
T_d:P_t	-19.8333	1.616	-12.271	0	-23.069	-16.598

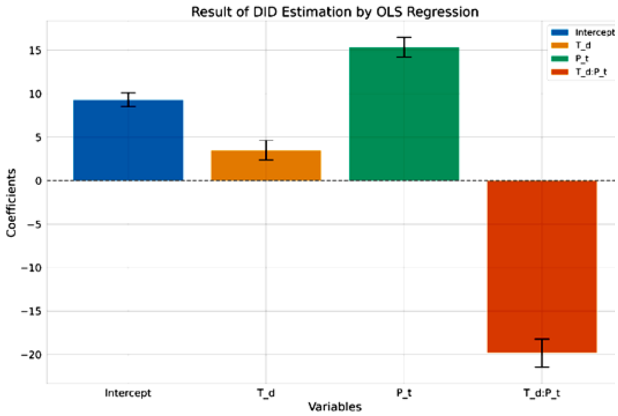

Figure 3. Result of difference-in-differences estimation by ordinary least squares regression (R).

Table 5 presents the results of the double difference (DID) estimation in the evaluation of the R indicator within the DISASTER Paradigm. DID estimation serves as a methodology that discerns the causal effect of a specific intervention or treatment, juxtaposing the alterations in outcomes pre and post the intervention between a treatment group and a control group [24].

The analysis demonstrates that the intercept value stands at 9.3125, epitomizing the predicted value of the dependent variable R when both Td and Pt are zero. The coefficient for Td is 3.5, delineating that for every unit increase in the Treatment variable, the value of R is augmented by 3.5 units. Analogously, the coefficient for Pt is 15.3542, denoting that each unit increase in the Post variable escalates the value of R by 15.3542 units. Lastly, the coefficient for the interaction term Td:Pt is -19.8333, inferring that the influence of Treatment on R is dependent on the value of Post, and specifically, when the value of Post is high, the effect of Treatment on R diminishes.

In summation, the DID estimation findings furnish evidence that both Treatment and Post exert a considerable impact on the R indicator in the DISASTER Paradigm, and the interplay between these variables is statistically meaningful.

DISCUSSION

This research was initiated leveraging the DISASTER paradigm to evaluate the efficacy of an educational system designed for medical professionals. Utilizing the Difference-in-Differences (DID) estimation predicated on the Ordinary Least Squares (OLS) regression, and conducted via Python programming, negative net utility (Td:Pt) emerged

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across the markers T, E, and R. This suggests that the intervention might not have successfully augmented the net utility for the targeted group.

Contrary to prior studies which deduced the impacts of similar educational programs using general DID-Estimation, the result of this investigation, grounded in a computational mathematical methodology, proffers a scholarly conclusion with enhanced precision [2]. The application of Python programming accentuated the scientific rigor and reliability of my conclusion, thereby bolstering the burgeoning realm of Computational Social Science.

The intricacies inherent to REM training, alongside the distinctive challenges specific to various medical sectors, may elucidate the observed outcomes. Prevailing literature underscores a propensity for tailored training programs to boost proficiency [2]. As such, I advocate for the development of strategies that can be customized to a myriad of medical specialties, aiming to more effectively equip medical personnel for real-world contexts.

The observed negative net utility could be attributed to either the inadequate execution of the educational initiative or a potential shortfall in participants' comprehensive engagement. This perspective is congruent with extant research which contends that the triumph of educational programs is significantly tethered to their implementation and the engagement magnitude of participants [13]. Probing deeper to unearth the fundamental causes for the program's inefficacy is essential, and strategies to enhance both execution and participation are paramount.

Recognizing the limitations of the DID estimation predicated on OLS regression is imperative. The model operates on the assumption that no external variables have influenced the outcomes, and that the treatment and control cohorts are analogous. Consequently, to surmount the constraints of this study based on OLS regression, I propose subsequent investigations employing DID estimations grounded on the Fixed Effect (FE) methodology [25-26]. Notwithstanding these inherent limitations, the insights proffered by this research are invaluable concerning the effectiveness of training programs for medical professionals.

By highlighting deficiencies in the program, avenues can be forged to elevate the efficacy of such initiatives, subsequently enhancing national radiation emergency readiness quality. Furthermore, the introduction of DID estimation predicated on OLS regression emerges as a pivotal tool in assessing training program efficacy, with its utility spanning beyond just the domain of radiation emergency medicine.

CONCLUSION

In conclusion, the analysis revealed that the intervention did not successfully augment the net utility for the targeted demographic, as manifested by negative net utilities across the three indices: T, E, and R. These findings not only provide more nuanced insights compared to preceding research but also make a significant contribution to the domain of computational social sciences, particularly through the adept application of Python programming. The insights garnered from this investigation illuminate the effectiveness of training programs at the nexus of the nuclear and medical sectors. t In essence, this research lays a foundational framework for the crafting of bespoke strategies that address the singular challenges endemic to the convergence of nuclear and medical sectors, thereby potentially elevating the effectiveness of corresponding programs.

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***Ethical consideration*:** All procedures and protocols followed in this study were in accordance with the ethical standards of the institution.

***Author contribution*:** Seokki Cha, Conceptualization, funding, data curation, methodology, manuscript writing & revision, data analysis, python programming, computational modeling.

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