Journal of Health, Medicine and Nursing
ISSN 2422-8419 An International Peer-reviewed Journal
Vol.116, 2024

Possible Benefits of Smart Application Technology Among BSN Students for Asthma Care: A Validation Study Using Confirmatory Factor Analysis and Structural Equation Modeling

Malachi Brannon
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: malachi.brannon@helenefuld.edu

Treshawna Cook
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: treshawna.cook@helenefuld.edu

Jennifer Diggs
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: jennifer.diggs@helenefuld.edu

Danielle Zilpa Juray
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: zilpa.kataev@helenefuld.edu

Chanho Kwak
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: chanho.kwak@helenefuld.edu

Sunita Paltoo
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: sunita.paltoo@helenefuld.edu

Jose Robert
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: jose.robert@helenefuld.edu

Tashanah Vallon (Corresponding Author)
Helene Fuld College of Nursing, NY, USA
24 E 120th Street, New York, NY 10035, USA
E-mail: tashanah.vallon@helenefuld.edu

Abstract

This study aims to evaluate the psychometric properties of the 17-item “Smart Applications for Asthma Care: Nursing Students’ Insights Survey,” which includes subscales such as “Being Mindful of the Client’s Breathing,” “Caring abilities of the student nurse,” and “Integrating smart application technology into client care.” The questionnaire measures the effectiveness of smart app technology in asthma patient care among nursing students. While the questionnaire demonstrates reliability through composite reliability, only the subscale “Integrating smart application technology into client care” exhibits convergent validity as confirmed by the confirmatory factor analysis (CFA). The results of the structural equation modeling (SEM) indicate a significant relationship between caring abilities and asthma knowledge, as evidenced by a strong positive path coefficient (β = 0.916, *p* = .006), suggesting that nursing students with higher levels of caring abilities tend to possess greater knowledge about asthma. However, no significant relationships arise between smart app use and either caring abilities (β = 0.007, *p* = 1.00) or asthma knowledge (β = 0.231, *p* = .227). Similarly, mindful breathing did not show a significant relationship with either caring abilities (β = 0.006, *p* = .999) or asthma knowledge. The results suggest that while caring abilities are positively associated with asthma knowledge, the use of smart apps and mindful breathing may not directly impact either caring abilities or asthma knowledge among nursing students in this study. Moreover, the relationship between smart app use and mindful breathing is not statistically significant. Pretest Q3 (0.83571), Posttest Q3 (0.86561), and Posttest Average (0.85415) have high R^2 values, indicating their significant predictive power in the performance of nursing students in this study. Further research is warranted to address these results, given the significant differences between the user and baseline structural models, and to optimize the integration of smart app technologies.

Keywords: structural equation modeling, confirmatory factor analysis, smart app, smart application, healthcare technology, nursing education, nursing students, asthma management
DOI: 10.7176/JHMN/116-03

Publication date: May 30th 2024

1. Introduction

There have been noteworthy revolutionary technological developments within the healthcare industry within the last several years. These developments have significantly impacted patient care practices (Kim et al., 2019). When we factor in the confirmatory factor analysis (CFA), potential nursing students and future healthcare professionals are also impacted by the new variables and dynamics.

This study is focused on observing and detailing the relationships and underlying influences among different elements. The factors that play into the relationship include the utilization of smart application technology for nursing education. Smart applications are utilized through smartwatches and smartphones which can be easily and readily accessed by the user. The crucial point is to deliver a structured approach integrating a quasi-experimental education tool with the oversight provided by senior nursing students.

Under the umbrella and structure of CFA, our goal is to verify or disprove the factors that contribute to the successful utilization of technology by nursing students. Additionally, we also want to analyze the influence of study variables on asthma patients and the quality of care through structural equation modeling (SEM).

2. Methods

In **Phase 1** we performed a CFA using Jamovi (ver. 2.3.26) to test our variables and confirm that it aligns with our theoretical model and study. Our sample size in the research was 34 participants. The CFA results underscore the reliability and internal consistency of the "Smart Applications for Asthma Care: Nursing Students' Insights Survey," providing a robust foundation for the study's results. The calculated Composite Reliability (CR) and Average Variance Extracted (AVE) metrics offer insights into the reliability and convergent validity of the instrument, essential for ensuring the accuracy and consistency of the measured constructs.

In **Phase 2** we performed a Structural Equation Model (SEM) again using Jamovi (ver. 2.3.26) to analyze the relationships between our latent variables. Our variables included were renamed in the following: "**Mindful Breathing**," "**Caring Abilities**," and "**Knowledge Asthma**". The Standardized Root Mean Square Residual (SRMR) and the Root Mean Square Error of Approximation (RMSEA) gives insight into whether our model agrees with the data we collected in our research.

3. Results

Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was conducted at the pretest to test the 17-item **Smart Applications for Asthma Care: Nursing Students' Insights Survey** based on a three-factor, single-order, multidimensional model. In Table 2, factor loadings ranged between 1 and 17 on Factor 1/Subscale: "**Being mindful of the client's breathing,**" between 1 and 4 on Factor 2/Subscale: "**Caring abilities of the student nurse**," and between 5 and 9 on Factor 3/Subscale: "**Integrating smart application technology into client care**". Except items 2 and 10 factor loadings were above the .50 threshold (Liao, Huang, & Wang, 2022). Alternatively, a loading factor value of > .30 was still a good item (Faradillah & Adlina, 2021) such as items 1, 3, 4, 5, and 6. These indicate that the degree of item relationships to their specific factor were adequate (Bean, 2021).

CFA Model fit was assessed with maximum likelihood (ML) for exact fit by chi-square index (χ^2) and approximate fit by standard root mean square residual (SRMR), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker–Lewis index (TLI). Specifically, exact fit was statistically significant, χ^2 (*df*) = 694.173, $p < .001$ indicating a good model fit. SRMR 0.195 was **unacceptable** based on the recommended value of < .08. RMSEA 0.279 (90% CI [0.209, 0.149]) was over the acceptable range of .05 to .08. CFI (0.753) was below the .95 cutoff. TLI 0.711 was below the .90 cutoff. (Liao, Huang, & Wang, 2022; Li, Huang, & Feng, 2020).

The Kaiser-Meyer-Olkin (KMO) test yielded an overall value of 0.764, indicating that the sampling adequacy is reasonably good for conducting factor analysis. This suggests that the data is suitable for further analysis. Additionally, Bartlett's test of sphericity was significant (χ^2 = 553.462, df = 136, $p < .001$), indicating that correlations between variables are sufficiently large for factor analysis to be appropriate.

The R^2 values provided indicate the proportion of variance explained by each individual item in the model. Higher R^2 values indicate that the item contributes more to explaining the variance in the subscale. In this case, items 3, 6, 7, 12, and 16 have relatively high R^2 values, ranging from 0.792 to 0.852. This suggests that these items have a stronger relationship with their subscales and contribute more to explaining its variance compared to other items. On the other hand, items 2, 5, 8, 9, 10, and 17 have lower R^2 values, indicating that they have weaker relationships with their subscales and contribute less to explaining its variance.

Factor loadings represent the strength and direction of the relationship between each indicator (or item) and its corresponding latent factor in a factor analysis model. In this analysis, each item is associated with one of three factors: "**Being mindful of the client's breathing**," "**Caring abilities of the student nurse**," and "**Integrating smart application technology into client care**."

The estimates of the factor loadings provide valuable insights into the contribution of each item to its respective latent factor. Higher factor loading values indicate a stronger relationship between the item and the latent factor. For example, items 1, 3, 6, 10, 11, 12, 13, 14, 15, 16, and 17 have high factor loading values, ranging from 0.793 to 0.960. This suggests that these items are strongly associated with their corresponding latent factors and contribute significantly to defining those factors.

On the other hand, items 2, 5, 7, 8, and 9 have relatively lower factor loading values, ranging from 0.354 to 0.674. While these items still contribute to their respective latent factors, their association is not as strong as those with higher factor loading values.

In Table 2, the composite reliability (CR) of each latent variable and the average variance extracted (AVE) were calculated using an Excel spreadsheet (available at https://www.analysisinn.com/post/how-to-calculate-average-variance-extracted-and-composite-reliability/). CR assessed the internal consistency of indicators within a single domain while AVE measured the amount of variance in the indicators explained by each domain compared with the variance explained by measurement error (Verdugo-Alonso et al., 2017). In Table 2, CR of the 3 domains/subscales were ≥ .70 (Cheung et al., 2023) in the following: "**Being mindful of client's breathing**" = 0.723; "**Caring abilities of the student nurse**" = 0.726; and "**Integrating smart application technology into client care**" = 0.955. AVE for first-order factors should be at least .50 (50%) to show convergent validity (Cheung et al., 2023; Nguyen et al., 2022). AVE was less than 50% in the subscales: Being mindful of the clients breathing (subscale 1); and Caring abilities of the student nurse (subscale 2) but it was greater in Integrating smart application technology into client care (subscale 3). The correlation coefficient between subscales should not exceed the square root of AVE (Dragan & Topolšek, 2014) to conclude discriminant validity. As shown in Table 2, subscale 3 met the criteria, except subscale 1 and 2.

Table 1

Composite reliability and average variance extracted per CBI subscale (N = 37)

Subscale	Factor Loading	CR	AVE
Being mindful of the client's breathing		**0.723**	**0.414**
1. I take and record accurate vital signs (count respiration for 1 full minute, listen and auscultate lung sounds, check oxygen saturation).	0.793		
2. I provide guidance and support to the client, if needed, to ensure their breathing is at a comfortable level.	0.354		
3. I facilitate and provide client with techniques or tools that can help them manage their breathing or treat any breathing issues (ex: use of incentive spirometer, rescue inhaler use).	0.779		
4. I provide a supporting and calming environment that enables the client to focus on their breathing.	0.544		
Caring abilities of the student nurse		**0.726**	**0.358**
5. I provide guidance and support to the client, if needed, to ensure their breathing is at a comfortable level during asthma care.	0.538		
6 In my role, I educate asthma patients on the proper use of inhalers and other devices, helping them manage their condition effectively.	0.791		
7. I actively monitor and assess asthma patients to identify potential triggers or worsening symptoms, taking prompt action as needed.	0.674		
8. I collaborate with the healthcare team and communicate patient progress and concerns effectively to ensure comprehensive asthma care.	0.514		
9. I am confident in my ability to provide appropriate care and support to asthma patients, based on my knowledge and skills acquired through nursing education.	0.396		
Integrating smart application technology into client care		**0.946**	**0.686**
10. I have tried using smart application technology in my nursing education to learn about asthma patient care, and it significantly improved my understanding of the subject.	0.836		
11. In my experience, using smart application technology as a learning tool enhanced my ability to retain and apply knowledge in asthma patient care.	0.801		
12. I have found that integrating smart application technology into my nursing education positively impacted my overall competence in managing asthma patients based on my experiences.	0.809		

13.	In my experience, smart application technology has been a valuable resource for improving my nursing skills specific to asthma patient care.	0.830
14	In my experience, smart application technology has been a valuable resource for improving my nursing skills specific to asthma patient care.	0.854
15.	Based on my experiences, I believe that smart application technology plays a crucial role in preparing me for real-world situations in asthma patient care.	0.820
16.	In my experience, the use of a smart application in asthma patient care has increased my confidence in making informed decisions and interventions during patient interactions.	0.899
17.	I have personally used a smart application to assist with asthma patient care, and it has improved the quality of care I provide by helping me stay updated on best practices and treatment options.	0.965

Note. Composite Reliability, CR; Average Variance Extracted, AVE

Structural Equation Modeling

The estimation method used for this analysis is diagonally weighted least squares (DWLS), with optimization performed through the nonlinear minimization subject to box constraints (NLMINB) method. The dataset comprises 37 observations, and the model includes 98 free parameters. Standard errors were computed robustly to account for potential violations of assumptions. The scaled test used is mean adjusted scaled and shifted. The analysis converged successfully after 295 iterations, indicating stability in the estimation process. These results suggest that the model was adequately optimized and provides reliable estimates for the given data.

These equations describe the relationships between latent variables and their predictors in the SEM framework, providing insights into how different variables interact within the model.

Equation 1:

efa (“efa1”) * Mindful Breathing + efa (“efa1”) * Caring Abilities + efa (“efa1”) * Smart App Use = ~ PretestQ1 + PretestQ2 + PretestQ3 + PretestQ4 + PretestQ5 + PostTestQ1 + PostTestQ2 + PostTestQ3 + PostTestQ4 + PostTestQ5 + PostTest2Q1 + PostTest2Q2 + PostTest2Q3 + PostTest2Q4 + PostTest2Q5

Note. Exploratory factor analysis, efa

Equation 2:

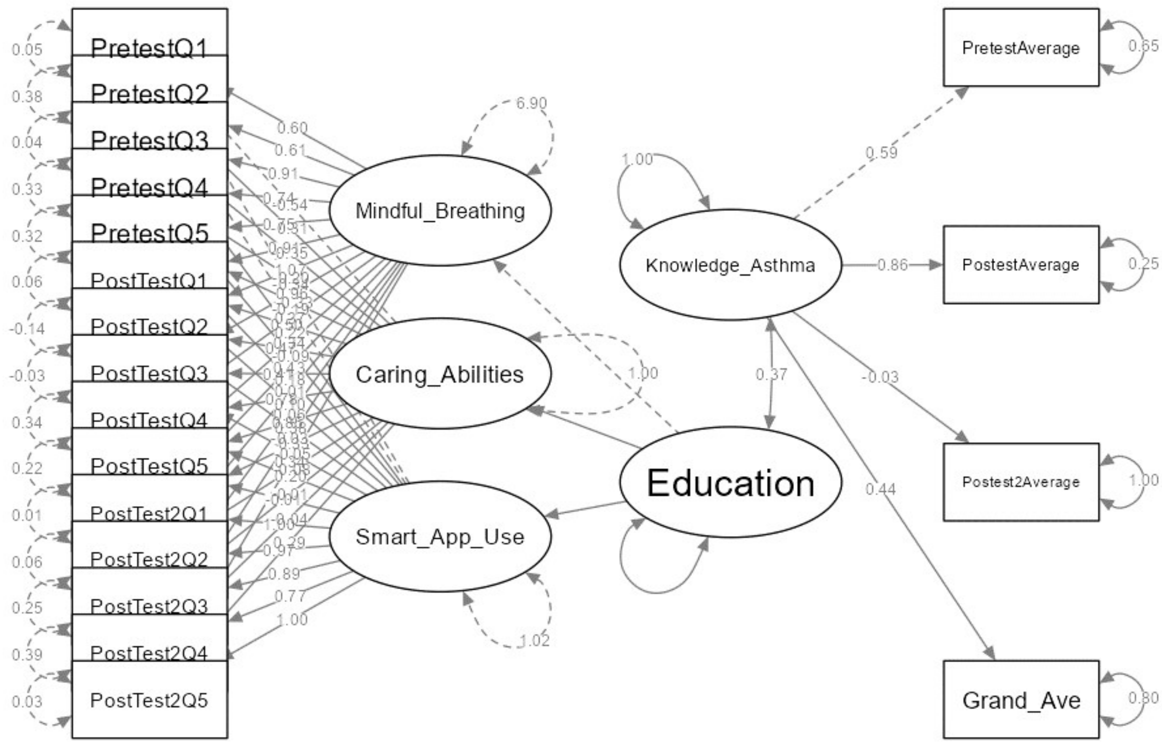
Knowledge Asthma = ~ PretestAverage + PostestAverage + Postest2Average + Grand Ave

Equation 3:

Education = ~ Mindful Breathing + Caring Abilities + Smart App Use

Figure 1

Path Diagram



Equation 1 represents a structural equation model (SEM) where latent variables are regressed on other latent variables and observed variables. The equation consists of three latent variables: “efa1,” “Knowledge Asthma,” and “Education.”

For the latent variable “efa1,” it is regressed on three exogenous variables: “Mindful Breathing,” “Caring Abilities,” and “Smart App Use”. The symbol ~ indicates a regression relationship. This equation implies that the latent variable “efa1” is influenced by “Mindful Breathing,” “Caring Abilities,” and “Smart App Use”.

The second equation represents the latent variable “Knowledge Asthma,” which is regressed on four observed variables: “PretestAverage,” “PostestAverage,” “Postest2Average,” and “Grand Ave”. This equation suggests that “Knowledge Asthma” is influenced by these observed variables.

The third equation represents the latent variable “Education,” which is regressed on three exogenous variables: “Mindful Breathing,” “Caring Abilities,” and “Smart App Use”. Similar to the first equation, this equation indicates that the latent variable “Education” is influenced by “Mindful Breathing,” “Caring Abilities,” and “Smart App Use”.

The model tests reveal significant differences between the User Model and the Baseline Model, with chi-square statistics of 230 and 18599, respectively, both yielding p-values below 0.001. Fit indices indicate that the User Model exhibits a better fit, with a Standardized Root Mean Square Residual (SRMR) of 0.21 and a Root Mean Square Error of Approximation (RMSEA) of 0.165 (95% CI: 0.134 - 0.196), while the Baseline Model shows comparable values. Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values are higher for the User Model (CFI = 0.994, TLI = 0.991) than the Baseline Model (CFI = 0.98, TLI = 0.971), indicating superior fit. The Goodness of Fit Index (GFI) for the User Model is 0.988, affirming a good overall fit.

Mardia's coefficients were employed to assess multivariate normality in the dataset, revealing a skewness coefficient of 4.39 ($z = 27.1$, $\chi^2 = 20$, $p = 0.133$) and a kurtosis coefficient of 21.3 ($z = -1.19$, $p = 0.235$). The skewness coefficient indicates a potentially right-skewed distribution, although not statistically significant at the conventional significance level of .05, while the kurtosis coefficient suggests a distribution slightly flatter than normal, also not statistically significant. These results collectively imply that the dataset does not significantly deviate from multivariate normality.

In Table 2, coefficient of determination or the R^2 measures the proportion of variance in the dependent variable that is predictable from the independent variables. Higher R^2 values indicate that a larger proportion of the variance in the dependent variable is explained by the independent variables. For instance, variables such as “PretestQ1,” “PretestQ3,” and “PostTest2Q1” have high R^2 values, indicating that they explain a significant portion of the variance in their respective outcomes, with values exceeding 0.9.

Conversely, some variables have lower R^2 values, suggesting that they explain a smaller proportion of the variance in their associated outcomes. For example, “PretestAverage,” “PostestAverage,” and “Postest2Average” have relatively low R^2 values, indicating that they have less predictive power in explaining the variance in their respective averages. This implies that other factors not included in the model may contribute more substantially to the variability in these averages.

Additionally, negative R^2 values for “Mindful Breathing,” “Caring Abilities,” and “Smart App Use” suggest that these variables do not contribute to explaining the variance in their associated outcomes within the model.

Table 2
Coefficient of Determination

Variable	R^2
PretestQ1	0.95415
PretestQ2	0.61728
PretestQ3	0.9586
PretestQ4	0.66778
PretestQ5	0.67828
PostTestQ1	0.93631
PostTestQ2	---
PostTestQ3	---
PostTestQ4	0.66351
PostTestQ5	0.77742
PostTest2Q1	0.99418
PostTest2Q2	0.94425
PostTest2Q3	0.75305
PostTest2Q4	0.61324
PostTest2Q5	0.96642
PretestAverage	0.34784
PostestAverage	0.74612
Postest2Average	0.00105
Grand_Ave	0.19743
Mindful Breathing	-5.8964
Caring Abilities	-0.0023
Smart App Use	-0.0157

Table 3 presents the estimates and confidence intervals for various latent variables and their observed indicators. For "Mindful Breathing," "PretestQ3" has the highest estimate of 2.39915 (SE = 0.338), followed by "PostTestQ2" with an estimate of 2.80892 (SE = 0.2318). "PostTest2Q2" has the lowest estimate of 0.01798 (SE = 0.4736), indicating the least impact among all variables. "Caring Abilities" to "PretestQ1" shows a significant negative impact with an estimate of -0.53808 (SE = 0.188), while "Smart App Use" to "PretestQ3" has a positive estimate of 0.21903 (SE = 0.2681). "Knowledge Asthma" to "PostestAverage" demonstrates a strong positive impact with an estimate of 1.46459 (SE = 0.3432). "Education" to "Mindful Breathing" has a fixed estimate of 1.13376, indicating a constant effect. Additionally, "Grand Ave" shows a moderate positive estimate of 0.75339 (SE = 0.249).

Table 3

Variables in the Structural Equation Model (N = 37)

				95% CI				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	***p***
Mindful Breathing	PretestQ1	1.56286	0.414	0.7514	2.3744	0.59513	3.7747	< .001*
	PretestQ2	1.60376	0.3911	0.8372	2.3703	0.6107	4.1005	< .001*
	PretestQ3	2.39915	0.338	1.7368	3.0615	0.91358	7.0989	< .001*
	PretestQ4	1.93934	0.3027	1.346	2.5326	0.73849	6.4066	< .001*
	PretestQ5	1.96317	0.3466	1.2838	2.6426	0.74756	5.6633	< .001*
	PostTestQ1	2.39873	0.1844	2.0373	2.7602	0.91342	13.0072	< .001*
	PostTestQ2	2.80892	0.2318	2.3547	3.2632	1.06962	12.1195	< .001*
	PostTestQ3	2.51775	0.1598	2.2046	2.8309	0.95874	15.7566	< .001*
	PostTestQ4	0.96304	0.4152	0.1493	1.7768	0.36672	2.3196	.020
	PostTestQ5	0.89225	0.4991	-0.086	1.8705	0.33976	1.7876	.074
	PostTest2Q1	1.13861	0.4222	0.3111	1.9661	0.43357	2.697	.007
	PostTest2Q2	0.01798	0.4736	-0.9103	0.9462	0.00685	0.038	.970
	PostTest2Q3	0.16967	0.4889	-0.7886	1.128	0.06461	0.347	.729
	PostTest2Q4	-0.07807	0.6118	-1.2772	1.121	-0.0297	-0.1276	.898
	PostTest2Q5	0.89331	0.4073	0.0949	1.6917	0.34016	2.193	.028
Caring Abilities	PretestQ1	-0.53808	0.188	-0.9066	-0.1695	-0.5375	-2.8617	.004
	PretestQ2	-0.30551	0.1641	-0.6271	0.0161	-0.3052	-1.862	.063
	PretestQ3	-0.34995	0.1564	-0.6565	-0.0434	-0.3496	-2.2378	.025
	PretestQ4	-0.20501	0.2014	-0.5997	0.1897	-0.2048	-1.018	.309
	PretestQ5	-0.33277	0.178	-0.6816	0.016	-0.3324	-1.8698	.062
	PostTestQ1	0.5042	0.1991	0.1139	0.8945	0.50362	2.5322	.011
	PostTestQ2	0.467	0.2062	0.0628	0.8712	0.46646	2.2643	.024
	PostTestQ3	0.40937	0.1818	0.053	0.7657	0.40889	2.2516	.024
	PostTestQ4	0.77635	0.1827	0.4183	1.1344	0.77546	4.2499	< .001*
	PostTestQ5	0.85426	0.1863	0.4892	1.2194	0.85328	4.5858	< .001*
	PostTest2Q1	0.33355	0.1102	0.1175	0.5496	0.33317	3.0261	.002
	PostTest2Q2	-0.08398	0.0911	-0.2625	0.0946	-0.0839	-0.9218	.357
	PostTest2Q3	-0.00791	0.1355	-0.2734	0.2576	-0.0079	-0.0584	.953
	PostTest2Q4	-0.03644	0.1481	-0.3267	0.2538	-0.0364	-0.2461	.806

	PostTest2Q5	0.28997	0.1546	-0.013	0.5929	0.28963	1.8758	.061
Smart App Use	PretestQ1	-0.34268	0.262	-0.8562	0.1709	-0.34	-1.3078	.191
	PretestQ2	-0.19384	0.276	-0.7348	0.3471	-0.1923	-0.7024	.482
	PretestQ3	0.21903	0.2681	-0.3065	0.7445	0.21733	0.8169	.414
	PretestQ4	-0.0857	0.2296	-0.5358	0.3644	-0.085	-0.3732	.709
	PretestQ5	0.18404	0.3134	-0.4301	0.7982	0.18261	0.5873	.557
	PostTestQ1	0.0959	0.3072	-0.5062	0.698	0.09515	0.3122	.755
	PostTestQ2	0.38114	0.3306	-0.2668	1.0291	0.37818	1.1529	.249
	PostTestQ3	-0.05404	0.3227	-0.6866	0.5785	-0.0536	-0.1674	.867
	PostTestQ4	0.20441	0.2562	-0.2977	0.7066	0.20282	0.7978	.425
	PostTestQ5	-0.00666	0.2421	-0.4811	0.4678	-0.0066	-0.0275	.978
	PostTest2Q1	1.00588	0.1496	0.7127	1.2991	0.99808	6.7247	< .001*
	PostTest2Q2	0.97717	0.0836	0.8134	1.1409	0.96959	11.6937	< .001*
	PostTest2Q3	0.89202	0.0939	0.708	1.076	0.8851	9.5012	< .001*
	PostTest2Q4	0.77868	0.1216	0.5404	1.0169	0.77264	6.4057	< .001*
	PostTest2Q5	1.00795	0.1376	0.7383	1.2776	1.00014	7.3264	< .001*
Knowledge Asthma	PretestAverage	1	0	1	1	0.58978		
	PostestAverage	1.46459	0.3432	0.7919	2.1373	0.86378	4.2673	< .001*
	Postest2Average	-0.05487	0.1974	-0.4418	0.3321	-0.0324	-0.2779	.781
	Grand_Ave	0.75339	0.249	0.2654	1.2414	0.44433	3.0258	.002
Education	Mindful Breathing	1.13376	0	1.1338	1.1338	---	---	---
	Caring Abilities	0.05879	0.0592	-0.0572	0.1748	---	0.9936	.320
	Smart App Use	0.15242	0.156	-0.1534	0.4582	---	0.9769	.329

Note. $p \leq .05$ (2-tailed), statistically significant; $*p \leq .001$, statistically highly significant; Confidence Interval, CI; Standardized Regression Coefficients, β

4. Discussion

Recording accurate vital signs, auscultating lung sounds, and monitoring oxygen saturation, has the highest factor loading score (0.793) under the subscale being mindful of the client's breathing. This is an essential component regarding asthma care. In order to properly treat asthma, we first need to have an idea of how critical or non-critical the situation is. The type of treatment that is required relies on accurate vital signs. The act of breathing and how much oxygen the body is receiving has a physiological impact on oxygenation level, heart rate, ventilation, and blood pressure. The primary outcome of this study was consistent with evidence that smart application technology education yields skills competency (caring behavior scores) among nursing students (Liao et al, 2022).

The findings of this study offer a nuanced understanding of integrating smart application technology into nursing education, specifically focusing on asthma care. The moderate caring behavior scores observed among senior nursing students reflect the complex interplay between technological interventions and traditional caregiving practices. This discussion delves into critical aspects of the results, addressing both the positive outcomes and areas that warrant consideration for future refinement.

The top three scores were based on a moderate caring behavior score, with the highest factor loading observed in the subscale "**Integrating smart application technology into client care**" ($\lambda = 0.96$). The subscale "**Being mindful of the client's breathing**" results show the second highest factor loading within the subscale is ($\lambda = 0.793$). The third highest score attained in the subscale of "**Caring abilities of the student nurse**" shows a score of ($\lambda = 0.791$).

The positive aspect of this study lies in the notable impact of smart application technology on the "**Integrating smart application technology into client care**" subscale. The high mean score ($\lambda = 0.965$) suggests that participants perceived significant benefits in improved competence and skills related to asthma patient care by incorporating technology. The item "**In my experience, smart application technology has been a valuable resource for improving nursing skills specific to asthma patient care**" particularly stands out, indicating the potential of technology to enhance the educational experience and skill acquisition in asthma management (λ = 0.972). The high mean score, (λ = 0.965), in the subscale, "**Integrating smart application technology into client care**" displayed by the participants, further supports that improved health outcome and sustained use of the health application which can be associated with patient engagement (Kim et al., 2019). Although the clinical trial conducted by Kim et al. (2019), focused on both the clinicians experience in the health advances for the patients and the patient's personal experiences. The results of the data gathered during the CFA greatly supported that technological advances in smart application can be integrated into client care and create positive results in return.

However, the study reveals a contrasting trend in the "**Being mindful of the client's breathing**" subscale. A decrease in scores in facilitating client breathing techniques (λ = 0.571) raises questions about technology integration's potential drawbacks or challenges. It prompts further consideration of whether over-reliance on technology might compromise fundamental aspects of nursing care, such as providing hands-on support and creating a supportive environment for patients.

The decline in scores in certain items within the "**Caring abilities of the student nurse**" subscale is noteworthy, emphasizing the importance of evaluating the holistic impact of technology on various dimensions of nursing care. Items such as "**I provide guidance and support to the client, if needed, to ensure their breathing is at a comfortable level during asthma care**" (λ = 0.854) and "**I actively monitor and assess asthma patients to identify potential triggers or worsening symptoms, taking prompt action as needed**" (λ = 0.865) saw decreases, indicating potential challenges in maintaining traditional caregiving aspects while incorporating technology.

The low significance in CFA from this study (Adejumo et.al, 2022) supports our findings that integration of smart technology does not strongly correlate to caring abilities of the student nurse ((λ =0.791). Yet, it can be inferred that continued integration of smart technology will lead to more nursing students being familiar with using it leading to an increase in caring abilities involving educating asthma patients.

By SEM, the "Knowledge Asthma" latent variable demonstrates significant positive relationships with observed variables "PretestAverage," "PostestAverage," and "Grand_Ave," indicating its sensitivity to changes in these measures. Conversely, "Postest2Average" does not significantly contribute to "Knowledge Asthma," as indicated by its non-significant estimate. The "Education" latent variable also displays notable relationships with its respective exogenous variables, with "Mindful Breathing" showing a particularly strong positive association. However, "Caring Abilities" and "Smart App Use" exhibit weaker and less consistent relationships with "Education," with smaller effect sizes and less significant *p*-values.

Despite the mixed results, the study contributes significantly to the evolving discourse on integrating technology into nursing education. It highlights the need for a balanced approach, where technology is a valuable supplement to traditional caregiving practices rather than a replacement. The observed decline in scores in certain domains prompts consideration of targeted interventions or additional training to address potential gaps in students' ability to integrate technology with hands-on care seamlessly.

Furthermore, the study's focus on asthma care is particularly relevant in the growing prevalence of chronic respiratory conditions. The positive impact observed in the "**Integrating smart application technology into client care**" subscale suggests that technology can be crucial in preparing nursing students for real-world situations in asthma patient care. Future research endeavors should explore the longitudinal effects of technology integration, considering how these experiences shape nursing practice beyond educational settings.

5. Conclusion

Integrating digital technology into nursing education holds substantial promise for enhancing asthma patient care and nursing students' educational experiences. Our research underscores students' increased competence and skills. The potential for improved asthma patient management and encompassing education is evident. While the study underscores the potential benefits of intelligent application technology in nursing education, particularly in asthma care, it also underscores the importance of cautious integration to preserve essential caregiving elements.

Author Contributions

All authors have read and agreed to the published version of the manuscript.

Funding Sources

This research has not received funds from any agency or institution.

Institutional Review Board Statement

The study was conducted according to Helene Fuld College's research ethics committee.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgement

We would like to thank the participants for their valuable time and participation in this study. We would also like to thank Dr. Joannes Paulus Tolentino Hernandez (https://orcid.org/0000-0002-3499-1821) for guiding us through this research study that we have completed.

References

Kim, J., Ryu, B., Cho, S., Heo, E., Kim, Y., Lee, J., Jung, S.Y., & Yoo, S. (2019). Impact of personal health records and wearables on health outcomes and patient response: Three-arm randomized controlled trial. *JMIR Mhealth Uhealth, 7*(1): e12070. https://doi.org/10.2196/12070

Liao, H. C., Huang, C. Y., & Wang, Y. H. (2022). Development and psychometric testing of a scale measuring caring behaviors for healthcare students and providers. *Medical Education Online*, *27*(1), 2066496. https://doi.org/10.1080/10872981.2022.2066496

Faradillah, A., & Adlina, S. (2021). Validity of critical thinking skills instrument on prospective Mathematics teachers. *Jurnal Penelitian dan Evaluasi Pendidikan, 25*(2), 126-137. http://dx.doi.org/10.21831/pep.v25i2.40662

Bean, J. (2021, October 13). Using R in social work research. The Ohio State University. https://bookdown.org/bean_jerry/bookdown_r_for_social_workers/confirmatory-factor-analysis.html

Li, N., Huang, J., & Feng, Y. (2020). Construction and confirmatory factor analysis of the core cognitive ability index system of ship C^2 system operators. *Plos One, 15*(8), e0237339. https://doi.org/10.1371/journal.pone.0237339

Verdugo-Alonso, M. A., Henao-Lema, C. P., Córdoba-Andrade, L., & Arias González, V. B. (2017). Dimensionality and internal structure of the Colombian version of the INICO-FEAPS quality of life scale. *Journal of Intellectual Disability Research, 61*(12), 1094-1103. https://www.researchgate.net/publication/320326481_Dimensionality_and_internal_structure_of_the_Colombian_version_of_the_INICO-FEAPS_quality_of_life_scale

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 1-39. https://doi.org/10.1007/s10490-023-09871-y

Nguyen, T. T. P., Truong, G. T. H., Nguyen, H. T. T., Nguyen, C. T. T., Dinh, D. X., & Nguyen, B. T. (2022). An instrument for measuring job satisfaction (VIJS): A validation study for community pharmacists in the context of the COVID-19 pandemic in Vietnam. *PLoS One, 17*(11), e0276918. https://doi.org/10.1371/journal.pone.0276918

Dragan, D., & Topolšek, D. (2014, June). Introduction to structural equation modeling: Review, methodology and practical applications. In *The International Conference on Logistics & Sustainable Transport* (Vol. 6, pp. 19-21). https://www.researchgate.net/profile/Dejan-Dragan-2/publication/267810858_Introduction_to_Structural_Equation_Modeling_Review_Methodology_and_Practical_Applications/links/545acf900cf25c508c319c8b/Introduction-to-Structural-Equation-Modeling-Review-Methodology-and-Practical-Applications.pdf

Adejumo, I., Patel, M., McKeever, T. M., & Shaw, D. E. (2022). Does inhaler technology improve adherence and asthma control? A pilot randomized controlled trial. *Annals of Allergy, Asthma & Immunology, 128*(6), 727-729. https://doi.org/10.1016/j.anai.2022.02.023