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The relationship between the pharmacist's role, patient understanding and satisfaction during the provision of a cost-effective pharmacist-led intervention

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Abstract

Rationale, Aims and Objectives: This study aimed to investigate the relationship between the pharmacist's role, patient understanding and satisfaction during the provision of a cost-effective pharmacist-led intervention using structural equation modelling (SEM). SEM is a group of statistical techniques used in different disciplines to model latent variables and evaluate theories.

Methods: A validated questionnaire was used to gather patient views on a pharmacist-led intervention. A conceptual model was developed to test the statistical significance of the relationship between patient understanding and satisfaction, the pharmacist's role and patient understanding, the pharmacist's role and patient satisfaction. In addition, the study evaluated the model's in-sample and out-of-sample predictive power. The analysis tested fours hypotheses (H): 1) There was no significant relationship between patient understanding and patient satisfaction; 2) There was no significant relationship between the pharmacist's role and patient understanding; 3) There was no significant relationship between the pharmacist's role and patient satisfaction; 4) The in-sample and out-of-sample predictive power of the model. Data were analysed using Smart-PLS software version 3.2.8.

Results: Two hundred and forty-six patients returned the questionnaire. Construct reliability, validity (Cronbach's alpha⟩0.70, ρA>0.70, ρC>0.70), average extracted variance (AVE⟩0.50) and discriminant validity (HTMT<0.85) were confirmed. The structural model and hypothesis testing results showed that all hypotheses were supported in this study. Path coefficients and effect sizes suggested that the pharmacist's role played a significant part in patient understanding (H2, β=0.650, f^2=0.730, p<0.001), which then influenced patient satisfaction (H1, β=0.474, f^2=0.222, p<0.001). The in-sample and out-of-sample predictive powers were moderate.

Conclusions: Patient satisfaction is becoming an integral component in healthcare provision and evaluation of healthcare quality. The results support using structural equation modelling to assess the link between the pharmacist's role and patient understanding and satisfaction when delivering cost-effective pharmacist-led interventions.

KEYWORDS
patient, pharmacist, PLS-SEM, role, satisfaction, understanding

1 | INTRODUCTION

Asthma is a chronic disease that affects adults and children all over the world[1-3] and is responsible for considerable global mortality and healthcare costs.[4] One in eight deaths in the European Union is from respiratory disease; 600,000 people in the EU die every day from respiratory conditions. The total yearly cost of respiratory diseases in the EU exceeds 380 billion euros, and the annual economic burden of asthma is 72 billion.[5] Many studies have advocated the role of pharmacists in asthma care. Numerous well-designed studies have been carried out on asthma[6-10]; however, very few provided evidence of effectiveness of pharmacist intervention?[11,12]

A large cluster randomized controlled trial conducted in Italy demonstrated the effectiveness and cost-effectiveness of the pharmacist-led intervention in asthma patients.[13] Further analysis showed that even a relatively minor impact of the asthma control test (represented by a three-point shift in the ACT score) was cost-effective.[14] During this project, patients', pharmacists' and GPs' feedback was collected, and a report and article were published.[15] However, the analysis did not look specifically at the interaction between the pharmacist's role and patient understanding and satisfaction during this bespoke pharmacist-led intervention.

Structural equation modelling (SEM) represents a group of statistical techniques that have become very popular in business and social sciences. Its ability to model latent variables, consider various measurement error forms, to consider various forms of measurement error, and evaluate entire theories makes it useful for different types of research.[16] SEMs can be divided into covariance-based (CB) and variance-based (VB) SEM. Hair et al.[17] suggested that the covariance-based structural equation model (CB-SEM) is a confirmatory approach that focuses on the model's theoretically established relationships and minimizes the difference between the model-implied and the sample covariance matrix. In contrast, PLS-SEM is a prediction-oriented VB approach that focuses on endogenous target constructs in the model and aims at maximizing their explained variance (e.g., looking at the coefficient of determination [R^2] value).[17] CB-SEM estimates model parameters using an empirical variance–covariance matrix, which is the method of choice if the hypothesized model has one or more common factors. Variance-based structural equation model (VB-SEM) first creates a proxy as a linear combination of observed variables and then estimates model parameters using these proxies. In addition, VB-SEM is the method of choice if the hypothesis contains composites. According to McDonald,[18] among the VB-SEM methods, Partial Least Squares (PLS) path modelling is considered the most fully developed, and Hair et al.[19] defined PLS-SEM as the 'Silver Bullet'. PLS-SEM is widely used in different disciplines, such as information system research, strategic management and marketing.[20] Urbonas et al.[21] used PLS-SEM to explore pharmacists' job satisfaction and effects of different indicators on job satisfaction. More recently Murshid and Mohaidin[22] explored the influence of pharmacists' expertise on prescribing decisions of physicians. Thus, SEM is becoming popular in pharmacy practice research, and other studies have been published in this area.[23,24] In 2019, Manfrin et al.[25] used PLS-SEM to evaluate a conceptual model for student satisfaction with team-based learning. Hannane et al.[26] looked at asthma patients' perception of their care pathway using SEM. Hindi et al.[27] developed and validated the Medicines Use Review (MUR) patient satisfaction questionnaire. This questionnaire was assessed using exploratory factor analysis. The themes identified were: (1) perceptions of the MUR service, (2) pharmacists' delivery of the MUR service, (3) the consultation room set, (4) and lack of awareness before having an MUR. This questionnaire presented some similarities to the one developed by Krska et al.[28] and used in our study. To the best of our knowledge, PLS-SEM has not been used to evaluate the relationships between the role of the community pharmacist, patient understanding and patient satisfaction during the provision of a cost-effective pharmacist-led intervention.

1.1 | AIM

To evaluate the relationship between the pharmacist's role and patient understanding and satisfaction during the provision of a bespoke, cost-effective pharmacist-led intervention using PLS-SEM.

1.2 | Conceptual model

Bollen[29] suggested that a path model is a diagram that displays the hypotheses and variable relationships estimated in an SEM analysis. Sarstedt et al.[30] contended that the structural model represents the structural paths between the constructs (variables). In contrast, the measurement models represent the relationships between each construct and its associated indicators. Sarstedt et al.[30] added that structural and measurement models in PLS-SEM are also referred to as inner and outer models. For the evaluation of the path and predictors of patient satisfaction, PLS-SEM was used, and a conceptual model was designed. PLS-SEM can be used for casual predictive analysis and for reflective and formative.[31] PLS-SEM is essentially a nonparametric method; therefore, the data do not need to be normally distributed. PLS-SEM handles data distribution using bootstrapping to find the statistical significance of the p values.[32] In our study, we aimed at using PLS-SEM to show how patient satisfaction is influenced by the pharmacist's role and patient understanding and to find out the predictive power of the model. The proposed model was analysed according to the flow chart developed by Sarstedt et al.[30] The analysis of the model was conducted in several stages:

- The measurement model aimed at revealing the relationships between latent indicators and their variables.
- The structural model aimed at evaluating the relationships between the latent variables.
- PLS-SEM prediction aimed at identifying potential predictors for the latent variables.

The conceptual model summarizes four hypotheses (H) that this study aimed to test after the provision of a bespoke effective and cost-effective pharmacist-led intervention for asthma patients (Figure 1).

Hypothesis 1 (*H1*): *There was no significant relationship between patient understanding and patient satisfaction.*

Hypothesis 2 (*H2*): *There was no significant relationship between the pharmacist's role and patient understanding.*

Hypothesis 3 (*H3*): *There was no significant relationship between the pharmacist's role and patient satisfaction.*

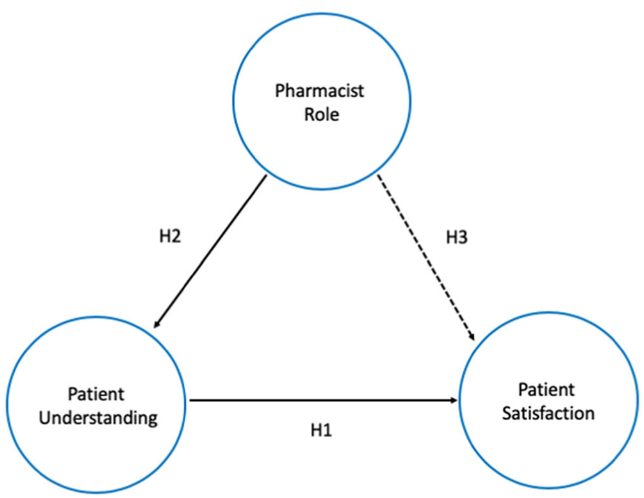

FIGURE 1 Conceptual model.

Hypothesis 4 (*H4*): *The in-sample and out-of-sample predictive power of the model.*

2 | METHODOLOGY

2.1 | Study design

This was an observational study.

2.2 | Population

All the information regarding the study setting, selection process of the participants, inclusion and exclusion criteria and the validated questionnaire used for data collection are published elsewhere.[15,28,33]

2.3 | Research instrument

The research instrument was a validated questionnaire aimed at gathering patient views on the medicine review service (pharmacist-led intervention), which had different types of questions, including 5-point Likert Scale questions (strongly agree, agree, neutral, disagree, strongly disagree), which were selected and included in this study.[28] Their selection was based on a pragmatic approach regarding the possible relevance of each question to one of the three constructs (latent variables): the pharmacist's role (perceived by patients), patient understanding and patient satisfaction (Table 1).

2.4 | Study power

The post hoc power of the study was estimated using G*Power version 3.1.9.3. A two-tailed t-test was conducted using multiple linear regression, with a fixed model and a single regression coefficient applying the following information: the number of patients enrolled in the study ($n = 246$), the number of predictors ($n = 4$), the effect size ($f^2 = 0.10$), and the probability of α error (0.05). The power of the study obtained was 99.85%, with a degree of freedom of 241, a critical $t = \pm1.97$, and a noncentrality parameter $\delta = 4.95$.

2.5 | Data collection and cleaning

Data were collected using paper questionnaires, but because these data were part of a national project in which all the data were collected using an online platform (Qualtrics), for consistency, it was decided to import the data into the same platform. The data set was then exported and uploaded into SPSS version 21 for data cleaning.

TABLE 1 Statements and latent variables.

Item	Statements	Latent variables
Q11	The pharmacist put me at ease	Pharmacist's role
Q14	I felt that I was given enough time for the MUR	
Q15	I had the full attention of the pharmacist during the MUR	
Q17	The pharmacist wanted to help me deal with any concerns I had about my medication	
Q18	I felt comfortable asking any questions I had about my medication	Patient understanding
Q19	I understood everything discussed during the MUR	
Q27	I was given an opportunity to discuss any problems I had during the MUR	
Q20	I feel I benefited from having the MUR	Patient satisfaction
Q24	I felt involved in all of the decisions made about my medications	
Q28	The MUR met my expectations	
Q29	I am happier with my medications after my review.	

Abbreviation: MUR, Medicines Use Review.

2.6 | Selection of an appropriate SEM

The Kolmogorov–Smirnov test was used for assessing normality. Data were not normally distributed, and the CB-SEM method was not recommended according to Hair et al.[19] Sarstedt et al.[34] suggested that VB-SEM is a more robust approach than CB-SEM for handling nonparametric data. Therefore, the SPSS data set was exported as a CVS file and then uploaded onto SmartPLS (version 3.2.8)[35]; the VB-SEM method recommended for non-normally distributed data was used for the analysis.

2.7 | Data analysis

The initial approach was to determine whether the model was formative or reflective, and according to Gudergan et al.[36] and Bollen and Ting,[37] the procedure of choice was confirmatory tetrad analysis (CAT). The implemented procedure needed at least four manifest variables (indicators) for each construct (latent variable). In our model, one of the constructs (patient understanding) had three manifest variables (indicators, Q18, Q19, Q20); therefore, it was decided to adopt a pragmatic approach applying a rule of thumb. If the indicators were interchangeable among themselves, the model was considered reflective, but if the indicators were not highly correlated and not interchangeable, the model was considered formative. The evaluation of the model was conducted using a reflective approach. The use of PLS-SEM allowed analysing the linear relationships between the latent constructs and the latent variables. Furthermore, PLS-SEM enabled the testing of several relationships, instead of analysing each relationship individually. According to Henseler et al.,[38] PLS-SEM consists of a two-step procedure involving evaluation of the outer measurement model and evaluation of the inner measurement model. The statistical validity of the model was assessed using the bootstrapping procedure with a statistical significance of $p \leq 0.05$. This procedure was repeated for 5000 samples.

2.7.1 | Measurement model assessment (evaluation of the outer model)

An iterative algorithm with 300 iterations (PLS algorithm) was used to determine the reliability (outer loading coefficients), internal consistency and validity of observed variables. Hair et al.[39] suggested that consistency evaluations are based on a single observed and construct reliability test while convergent and discriminant validity are used for validity assessment.

The first step aimed at observing the variables' loading coefficients; an outer loading coefficient, values ≥0.70, was recommended, but values of 0.40 or higher were considered acceptable for exploratory research, as in our case. Furthermore, indicators with loading above 0.70 indicate that the construct explains over 50% of the indicator variance.[40]

The second step required the evaluation of the internal consistency and reliability using Cronbach's $\alpha \geq 0.70$ as the lower bound, composite reliability (CR ≥ 0.70) using Dijkstra–Henseler's rhoA (ρ_A) as the indicator of true reliability,[41] and Dillon-Goldstein's rho$_C$ (ρ_C) as the upper bound. These assumptions were suggested by Tenenhaus et al.[42] and Hair et al.[43] Values of Cronbach's α and CR of at least 0.70 are required, although 0.6 are accepted.

The third step looked at convergent validity, which measures the extent to which a construct converges in its indicators by explaining the items' variance.[40] The convergent validity was assessed using the average variance extracted (AVE) for all items associated with each construct. AVE was calculated as the mean of the squared loadings for all indicators associated with a construct. The value of AVE ≥ 0.50 indicates that, on average, the construct explains over 50% of the variance of its items.[44]

The fourth step assessed the discriminant validity, which discriminates the extent to which a construct is empirically distinct from other constructs in the path model, in terms of correlation with other constructs and in terms of how distinctively the indicators represent only a single construct. The heterotrait–monotrait (HTMT) ratio of correlations is a new method for assessing discriminant validity in PLS-SEM and represents one of the key building blocks of model evaluation. According to Henseler et al.,[45] if discriminant validity is not established, researchers cannot be certain that results confirming hypothesized structural paths are real or whether they are merely the result of statistical discrepancies. It seems that the HTMT criterion outperforms classic approaches to discriminant validity assessment, such as the Fornell-Larcker criterion and (partial) cross-loadings, which are largely unable to detect a lack of discriminant validity. Henseler et al.[45] argued that there are two ways of using HTMT to assess discriminant validity: (1) as a criterion and (2) as a statistical test. The use of HTMT as a criterion implies that there is a predefined threshold, and if the value of HTMT is higher than the threshold, then there is a lack of discriminant validity. The suggested threshold is 0.85 (HTMT.85). The second option is using HTMT based on its statistical discriminant validity test (HTMTinference). The use of the bootstrapping procedure allows for construction of a confidence interval for HTMTinference. A confidence interval which contains the value of one is a sign of a lack of discriminant validity.

2.7.2 | Structural model assessment (evaluation of the inner model)

The collinearity among constructs represents the level of correlation between the two constructs. The variance inflation factor (VIF) indicates the level of collinearity, for example, when two constructs are highly correlated. The VIF was assessed by conducting a regression of each indicator on all other indicators in the same measurement model. The critical value of VIF is >5, but when it is >3, it also requires caution. Therefore, low VIF values (<3) represent good values.[19,43] Two types of predictions were generated and analysed: in-sample and out-of-sample prediction. The in-sample prediction was conducted by analysing the coefficient of determination (R^2) and the effect size (f^2). This analysis provides explanatory power, using the data set to estimate the model and predict observations from this data set. The value of R^2 measures the variance that is explained in each endogenous construct, and for this reason, it represents the 'in-sample predicting power' (explanatory power).[46,47] R^2 values range from 0 to 1; they depend on the discipline, but as a rule of thumb, $R^2 \approx 0.25$ is regarded as weak, $R^2 \approx 0.50$ moderate, and $R^2 \approx 0.75$ strong predictive power.[19,38] Furthermore, R is a function of the number of predictor constructs, and the higher the number of predictors, the higher R^2.[48] The effect size (f^2) assesses how strongly one exogenous construct contributes to explaining a specific endogenous construct in terms of R^2. According to Cohen,[49] the effect size is regarded as weak ($0.02 \le f^2 \le 0.15$), moderate ($0.15 \le f^2 \le 0.35$), and strong ($f^2 \ge 0.35$).

The procedure was conducted to assess the predictive power, which allows the model's estimates to predict new observations (e.g., future observations). Predictive relevance, also known as predictive power (Q^2), was used for this analysis. The value of Q^2 could be within different ranges, weak ($0.02 \le Q^2 \le 0.15$), moderate ($0.15 \le Q^2 \le 0.35$), and strong ($Q^2 \ge 0.35$) predictive power. Two main procedures can be followed for the calculation of Q^2, the first is blindfolding, and the second is PLSpredict. Sarstedt et al.[29] suggested that the value of Q^2 using blindfolding does not produce a true measure of out-of-sample prediction as blindfolding does not omit entire observations but only data points. If the obtained Q^2 values are >0, they are meaningful. Therefore, this value of Q^2 can only be partly considered a measure of out-of-sample prediction because the sample structure remains largely intact in its computation.[29] Shamueli et al.[50] introduced a new approach for out-of-sample prediction, which is now embedded into SmartPLS under the function PLSpredict. PLSpredict rests on the principle of K-fold cross-validation[58]. The procedure splits the data set into K equal parts ($K = 10$ in our case) and estimate the model K-times on K-1 data sets using r as the number of repetition ($r = 10$ in our case because it is a good trade-off between accuracy and running time). In this case, if $Q^2 > 0$, it means that the model (PLS) outperforms the most naïve benchmark represented by the linear model (LM). Furthermore, an important indication of the predictive power is represented by the comparison between the root mean squared error (RMSE) of prediction values obtained with PLSpredict versus the RMSE values obtained with (LM). Let us suppose the PLS yields higher prediction errors than the LM model in terms of RMSE for all values. In that case, this means no predictive power, the majority (low predictive power), the minority or the same (medium predictive power), or none of the indicators (high predictive power). Therefore, in our study, we adopted PLSpredict. All the results were deemed to be statistically significant with a $p \le 0.05$.

2.8 | Invitation letter

Italian community pharmacists contacted all their patients (895) who received the pharmacist-led intervention (MUR) service and invited them to complete a paper questionnaire. An invitation and an information letter were given to patients, explaining what was requested. Patients were asked to bring the questionnaire back to the pharmacy to ensure pharmacists did not see responses; the pharmacists then collected all the questionnaires and posted them to Medway School of Pharmacy for analysis using individually sealed envelopes.

2.9 | Data storage/confidentiality/anonymity

In terms of data storage, contact sheets and consent forms containing personal information were filed in a secure cabinet separate from any other participant data collected, to which only the research team could have access. Data obtained from the mail questionnaire were coded and stored electronically on a computer system in a directory which is password protected. All electronic data were password protected and accessible only to the researcher. All data were treated following the requirements of the Data Protection Act (1998); they were anonymized and stripped of any identifiable references to the participants.

3 | RESULTS

3.1 | Population demographics

Table 2 presents the demographic profile of the respondents, which shows the frequency and percentage of patients who replied to each statement. Two hundred and forty-six patients provided information, which gives a response rate of 27.5% (246/895). Only one patient failed to identify the location of residence, and one patient did not select the gender, leaving us with 245 valid cases. Fifty six point seven percent ($n = 139$) of patients were female and 43.3% ($n = 106$) were male. Two hundred and forty-four patients indicated their age, and two cases were missing. Patients' ethnicity was recorded by 244 people, leaving only two missing cases. The patient population was heavily dominated by white patients, 98.4% ($n = 240$), 1.2% ($n = 3$) classified themselves as mixed and 0.4% ($n = 1$) as black. Nearly one patient out of two (44.9%) completed the primary and a few years of secondary school, only eight patients did not go to school, and in only three cases the information was missing. Figure 2 shows the path model generated using the PLS algorithm.

3.1.1 | Model

Figure 2 represents the model. The values inside the circles represent the coefficient of determination (R^2). The values overlapping the arrows pointing towards the rectangles represent the outer loading coefficients. The values overlapping the arrows between the circles (constructs) represent the path coefficients (standardized β = β coefficients).

3.1.2 | Measurement model assessment (evaluation of the outer model)

All the values presented in Table 3 have shown that the model has both construct reliability and validity. Only 3 out of 11 loading coefficients were just below 0.70 (Q11, Q20 and Q24). Cronbach's α, ρ_A, ρ_C and AVE were all above the recommended thresholds.

The more conservative approach (HTMT85) showed that all three HTMT values were <0.85 (Table 4). The HTMT inference was calculated with the bootstrap routine, also using the bias-corrected and accelerated bootstrap (Bca) procedure with a 95% confidence interval. All the upper limits of the confidence intervals were lower than 1 (Table 4). The HTMT values were within the recommended thresholds; therefore, discriminant validity was achieved.

TABLE 2 Demographic profile of the respondent patients.

Patient characteristics		Number (%)
Place of residence	Brescia	76 (31.0)
	Pistoia	68 (27.8)
	Treviso	63 (25.7)
	Torino	38 (15.5)
		(Missing 1)
Sex	Male	106 (43.3)
	Female	139 (56.7)
		(Missing 1)
Age	18–30	20 (8.2)
	31–40	20 (8.2)
	41–50	26 (10.7)
	51–60	48 (19.7)
	61–70	51 (20.9)
	71–80	58 (23.8)
	>80	21 (8.5)
		(Missing 2)
Ethnicity	White	240 (98.4)
	Black	1 (0.4)
	Mixed	3 (1.2)
		(Missing 2)
Education	Primary/few years of secondary	109 (44.9)
	Secondary completed	73 (30.0)
	Bachelor's degree	26 (10.7)
	College further education	20 (8.2)
	None	8 (3.3)
	Still studying	4 (1.6)
	Higher degree	3 (1.2)
		(Missing 3)

Note: Percentages were calculated based on the number of responses.

3.1.3 | Structural model assessment (evaluation of the inner model)

The analysis of the collinearity among constructs showed that the VIF between patient understanding and patient satisfaction was 1.73, the pharmacist's role and patient satisfaction 1.73 and the pharmacist's

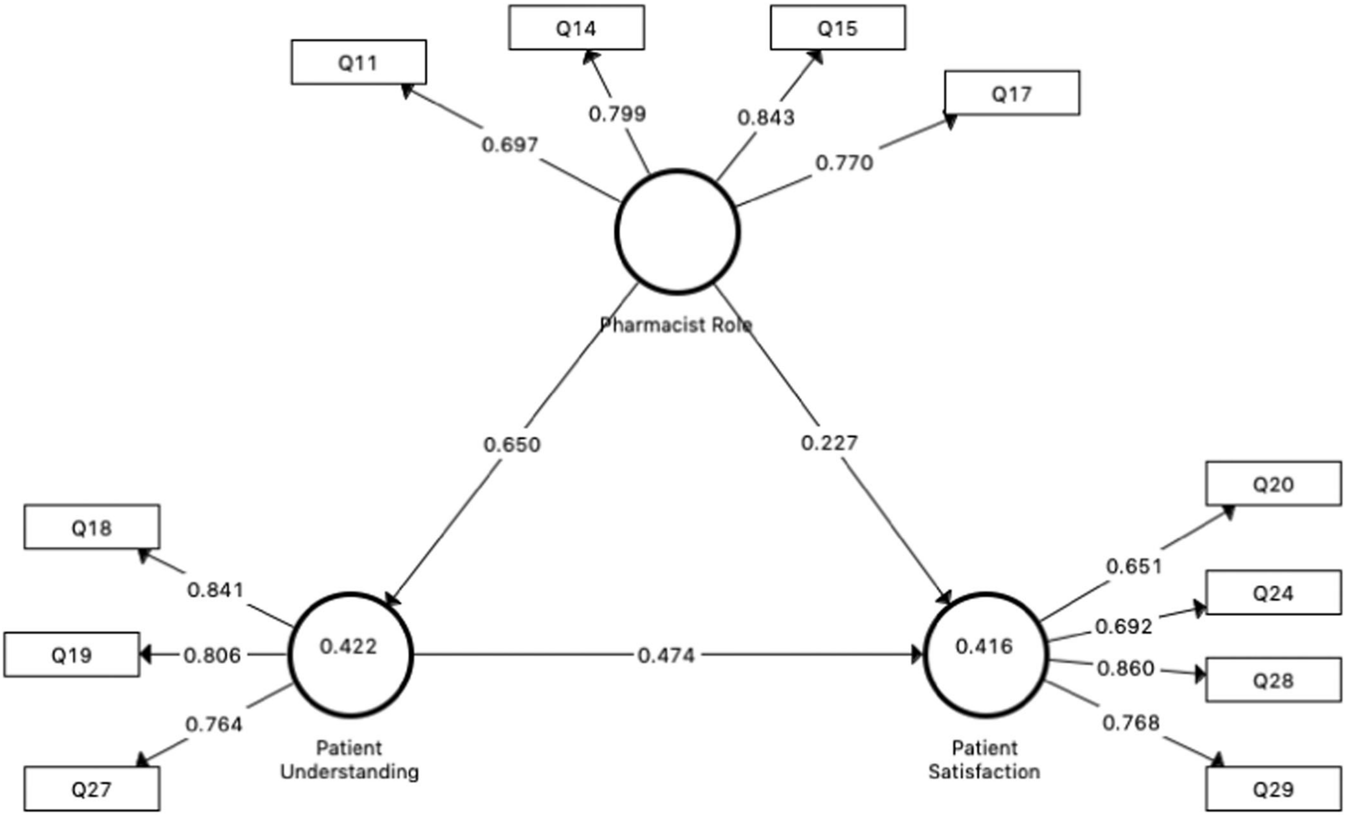

FIGURE 2 Path model.

TABLE 3 Construct reliability and validity.

Main constructs	Items	Loadings (≥0.70)	CA (>0.70)	ρ_A (0 > 70)	ρ_C (>0.70)	AVE (>0.50)
Pharmacist's role	Q11	0.697	0.784	0.794	0.860	0.607
	Q14	0.799				
	Q15	0.843				
	Q17	0.770				
Patient understanding	Q18	0.841	0.727	0.731	0.846	0.647
	Q19	0.806				
	Q27	0.764				
Patient satisfaction	Q20	0.651	0.727	0.794	0.833	0.558
	Q24	0.692				
	Q28	0.860				
	Q29	0.768				

Abbreviations: AVE, average variance extracted. Reliability measures: CA, Cronbach's α *(lower bound)*; ρA, true reliability; ρ_C (upper bound).

role and patient understanding 1.00. All the VIF values were well <3; the model did not present collinearity issues.

All three path coefficients were positive and statistically significant; the higher was linked with H2, and the lower was H3 (Table 5). The effect sizes were statistically significant and strong for H2 ($f^2 = 0.730$), moderate for H1 ($f^2 = 0.222$) and weak for H3 ($f^2 = 0.051$). The direct effect of the pharmacists' role in achieving patient satisfaction was 0.227. The indirect effect was 0.308 (95% CI 0.204; 0.432; $p < 0.001$). The total effect was 0.535 (95% CI 0.433; 0.632; $p < 0.001$).

The R^2 value for patient understanding was slightly higher than the one for patient satisfaction, but both coefficients were

TABLE 4 Discriminant validity.

Constructs	HTMT	95% CI	95% CI BCa
Patient understanding-patient satisfaction	0.813	[0.683; 0.935]	[0672; 0.925]
Pharmacist role-patient satisfaction	0.674	[0.540; 0.801]	[0.532; 0.793]
Pharmacist role-patient understanding	0.846	[0.757; 0.929]	[0.753; 0.926]

Abbreviations: BCa, bias-corrected and accelerated bootstrap; CI, confidence interval; HTMT, heterotrait–monotrait ratio of correlation.

TABLE 5 Significance and relevance of the path coefficients (standardized β).

Hypothesis path	Standardized β	*t* Value	95% CI	95% BCa CI	*p* Value	Effect size (f^2)
Patient understanding-patient satisfaction (H1)	0.474	6.017	[0.326; 0.630]	[0.304; 0.614]	<0.001	0.222
Pharmacist role-patient understanding (H2)	0.650	17.354	[0.577; 0.724]	[0.563;0.714]	<0.001	0.730
Pharmacist role-patient satisfaction (H3)	0.227	2.730	[0.059; 0.384]	[0.062;0.387]	0.006	0.051

Note: *t* Value (*t* statistics) thresholds: ±1.97.
Abbreviations: BCa, bias-corrected and accelerated bootstrap; CI, confidence interval.

TABLE 6 Coefficients of determination (R^2).

Main construct	Coefficient of determination (R^2)	*t* Value	95% CI	95% BCa CI	*p* Value
Patient satisfaction	0.416	7.657	[0.323; 0.536]	[0.300; 0.512]	<0.001
Patient understanding	0.422	8.657	[0.333; 0.524]	[0.317; 0.509]	<0.001

Note: *t* Value (*t* statistics) thresholds: ±1.97.
Abbreviations: Bca, bias-corrected and accelerated bootstrap; CI, confidence interval.

TABLE 7 Out of sample predictive power.

Code	Statements	RMSE (PLS)	Q^2 (PLS)	RMSE (LM)	Q^2 (LM)
Q18	I felt comfortable asking any questions I had about my medication	0.498	0.353	0.507	0.330
Q28	The MUR met my expectations	0.607	0.250	0.615	0.229
Q27	I was given an opportunity to discuss any problems I had during the MUR	0.625	0.228	0.622	0.235
Q19	I understood everything discussed during the MUR	0.656	0.210	0.656	0.209
Q29	I am happier with my medications after my review	0.703	0.180	0.708	0.167
Q20	I feel I benefited from having the MUR	0.825	0.107	0.821	0.115
Q24	I felt involved in all of the decisions made about my medications	0.862	0.051	0.866	0.041

Note: Predictive power according to Q^2: $0.02 \le Q^2 < 0.15$ (Weak); $0.15 \le Q^2 < 0.35$ (Moderate); ≥0.35 (Strong).
Abbreviations: LM, linear model; MUR, Medicines Use Review; PLS, partial least squares; RMSE, root mean squared error.

statistically significant. Furthermore, the model showed a moderate in-sample predictive power (Table 6).

The predictive power (Q^2) values of the PLS analysis were >0, indicating that the model outperforms the most naïve benchmark (e.g., the indicator means from the analysis sample) of the LM. The analysis compared the RMSE generated by PLSpredict with the RMSE of an LM. Four out of seven RMSE values (Q18, Q28, Q24, Q29) were lower in the PLSpredict model, one was equal to the LM (Q19), and three were higher. The results suggested that this model has a medium out-of-sample predictive power (Table 7).

4 | DISCUSSION

The number of patients who participated in this study was 246; 57% were female and 43% male. A conceptual model was designed aiming to test and evaluate four hypotheses; three (H1, H2, H3) were related to the path coefficients and one (H4) to the in-sample and out-of-sample predicting power of the model. Three constructs (latent variables) were included in the model, pharmacist role, patient understanding and patient satisfaction. One construct (patient understanding) had less than four manifest variables (indicators), and for this reason, it was not possible to conduct a CAT for assessing the nature of each construct, whether formative or reflective. Thus, a pragmatic approach was adopted using a reflective model to assess the outer model and inner model structure. A positive path coefficient was found for each hypothesis, suggesting that patient understanding had a positive influence on patient satisfaction (H1), pharmacist role had a positive effect on patient understanding (H2) and patient satisfaction (H3). In our model, the largest path coefficient was between pharmacist role and patient understanding (0.650) the smallest was between pharmacist role and patient satisfaction (0.227), suggesting that patient satisfaction was driven by patient understanding. The higher effect size (f^2) was for pharmacist role and patient understanding and the smallest for pharmacist role and patient satisfaction, suggesting that the pharmacists played a major part in patient understanding. Manfrin and Krska[15] conducted a study with a large number of patients ($n = 1711$) comparing the number and type of pharmaceutical care issues (PCI) that pharmacists identified in two different studies using the same pharmacist-led intervention and found that patient education was the most popular. A PCI is an element of pharmaceutical need to be addressed by the pharmacist.[51,52] Patient education is a PCI which represents the need the patient has to understand; similar results were found in other studies conducted in Denmark[53] and Germany.[54] Wang et al.[55] explored the pathways to 'outpatients' satisfaction with health care in Chinese public hospitals using a PLS model. In this study, the 'patients' experience of professional competence was strongly related to their satisfaction. In our study, pharmacist's role had a direct positive influence on patient understanding, which was positively linked to patient satisfaction. Amankwah et al.[56] looked at modelling the mediating effect of the healthcare healing environment on core healthcare delivery and patient satisfaction in Ghana. The data were analysed using SmartPLS, and the procedure was similar to the one used in our study; they assessed the in-sample predictive power but not the out-of-sample. Their finding confirmed that the healthcare healing environment mediated patient satisfaction. A study conducted in Qatar aimed at measuring patient's satisfaction with pharmaceutical services at a public hospital established, with statistical evidence, that patient satisfaction was positively influenced by pharmacist attitude and medication counselling.[57] Another study conducted in Turkey used SEM to look at factors affecting patient satisfaction and suggested that persons with a higher level of education were less satisfied when compared with those with a lower level of education.[58] In our study, we did not perform this comparison. Still, it is important to recognize that the level of education could have a relevant impact on patient perception and satisfaction.

5 | CONCLUSIONS

Hasan et al.[59] suggested that patient satisfaction is becoming an integral component in the health care provision and evaluation of the quality of health care. They added that patient satisfaction will be used in the future for performance assessment and reimbursement. Furthermore, Hasan et al.[59] suggested that patient satisfaction could be a predictor of health-related behaviour. In our study, the pharmacist's role demonstrated, a positive impact on patient understanding, which has driven patient satisfaction in our model. Our results support the use of PLS-SEM to assess the influence of pharmacists' role on patient's understanding and satisfaction when delivering effective and cost-effective pharmacist-led. Adittionally, PLS-SEM could be consider for the analysis other pharmacit-led interventions and their influence on patients understanding and satisfaction using larger samples and different conditions in primary and secondary care.

5.1 | Strengths and limitations

This study aimed to assess the effect of the pharmacist's role on patient understanding and patient satisfaction. To the best of our knowledge, this is the first attempt to evaluate these three dimensions after the provision of an effective and cost-effective pharmacist-led intervention in asthma patients using PLS-SEM. The conceptual model was simple, showing the effect of the pharmacists' role on the patients' understanding and satisfaction. This study has the following limitations: the selection of the questions, which was based on a pragmatic approach and the number of manifested variables that for one construct was three and for this reason, it was not possible to perform a CAT for assessing either the formative or reflective nature of each construct.

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CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

Data supporting the conclusions of this article can be found in the University of Central Lancashire (UCLan) Academic Repository (CloK).

ETHICS STATEMENT

Ethical approval was obtained from the University of Kent Faculty Research Ethics Committee (ref. No 024S12/13) by the Principal Investigator (Andrea Manfrin). The study participants were patients who received the MUR service. Return of the questionnaire to the pharmacist implied consent for its use in the evaluation. Written consent for publishing the results was obtained from patients and pharmacists before their enrolment in the study.

REFERENCES

1. Global Initiative for Asthma (GINA). Global strategy for asthma management and prevention. Accessed July 2017. 2014. http://www.ginasthma.org
2. Masoli M, Fabian D, Holt S, Beasley R. The global burden of asthma: executive summary of the GINA Dissemination Committee Report. *Allergy*. 2004;59(5):469-478. doi:10.1111/j.1398-9995.2004.00526.x
3. Nunes C, Pereira AM, Morais-Almeida M. Asthma costs and social impact. *Asthma Res Pract*. 2017;3(1):1. doi:10.1186/s40733-016-0029-3
4. Pavord ID, Beasley R, Agusti A, et al. After asthma: redefining airways diseases. *Lancet*. 2017;391(10118):350-400.
5. European Respiratory Society. European Lung White book. The economic burden of lung disease. Accessed 10 September 2015. 2016. http://www.erswhitebook.org/chapters/the-economic-burden-of-lung-disease/
6. Barbanel D. Can a self-management programme delivered by a community pharmacist improve asthma control? A randomised trial. *Thorax*. 2003;58(10):851-854.
7. Bunting BA, Cranor CW. The asheville project: long-term clinical, humanistic, and economic outcomes of a community-based medication therapy management program for asthma. *J Am Pharm Assoc*. 2006;46(2):133-147.
8. Emmerton L, Shaw J, Kheir N. Asthma management by New Zealand pharmacists: a pharmaceutical care demonstration project. *J Clin Pharm Ther*. 2003;28(5):395-402.
9. McLean W, Gillis J, Waller R. The BC community pharmacy asthma study: a study of clinical, economic and holistic outcomes influenced by an asthma care protocol provided by specially trained community pharmacists in British Columbia. *Can Respir J*. 2003;10:195-202.
10. Mehuys E, Van Bortel L, De Bolle L, et al. Effectiveness of pharmacist intervention for asthma control improvement. *Eur Respir J*. 2008;31(4):790-799.
11. Armour C, Bosnic-Anticevich S, Brillant M, et al. Pharmacy Asthma Care Program (PACP) improves outcomes for patients in the community. *Thorax*. 2007;62:496-592.
12. García-Cárdenas V, Sabater-Hernández D, Kenny P, Martínez-Martínez F, Faus MJ, Benrimoj SI. Effect of a pharmacist intervention on asthma control. A cluster randomised trial. *Respir Med*. 2013;107(9):1346-1355.
13. Manfrin A, Tinelli M, Thomas T, Krska J. A cluster randomised control trial to evaluate the effectiveness and cost-effectiveness of the Italian Medicines Use Review (I-MUR) for asthma patients. *BMC Health Serv Res*. 2017;17:300. doi:10.1186/s12913-017-2245-9
14. Tinelli M, White J, Manfrin A. Novel pharmacist-led intervention secures the minimally important difference (MID) in Asthma Control Test (ACT) score: better outcomes for patients and the healthcare provider. *BMJ Open Respir Res*. 2018;5:e000322. doi:10.1136/bmjresp-2018-000322
15. Manfrin A, Krska J. 'Pharmacists' and 'Patients' views and feedback on Italian Medicines Use Review (I-MUR). *Eur J Pers Cent Healthc*. 2018;6(2):286-296
16. Henseler J, Hubona G, Ray P. Using PLS path modeling in new technology research: updated guidelines. *Ind Manag Data Syst*. 2016;116(1):2-20.
17. Hair J, Sarstedt M, Pieper T, Ringle C. The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. *Long Range Plann*. 2012a;45(5-6):320-340. doi:10.1016/j.lrp.2012.09.008
18. McDonald RP. Path analysis with composite variables. *Multivar Behav Res*. 1996;31(2):239-270.
19. Hair JF, Ringle CM, Sarstedt M. PLS-SEM: indeed a silver bullet. *J Mark Theory Pract*. 2011;19(2):139-152. doi:10.2753/MTP1069-6679190202
20. Hair J, Sarstedt M, Ringle C, Mena J. An assessment of the use of partial least squares structural equation modeling in marketing research. *J Acad Mark Sci*. 2012b;40(3):414-433. doi:10.1007/s11747-011-0261-6.
21. Urbonas G, Kubilienė L, Urbonienė A. Pharmacists' job satisfaction and its effect on dispensing precaution taken at community pharmacies. *Sveikatos mokslai*. 2015;25:17-21. doi:10.5200/sm-hs.2015.043
22. Murshid MA, Mohaidin Z. Influence of the expertise, collaborative efforts and trustworthiness of pharmacists on the prescribing decisions of physicians. *J Pharm Pract Res*. 2019;49(2):150-161. doi:10.1002/jppr.1492
23. Nitadpakorn S, Farris KB, Kittisopee T. Factors affecting pharmacy engagement and pharmacy customer devotion in community pharmacy: a structural equation modeling approach. *Pharm Pract*. 2017;15(3):999. doi:10.18549/pharmpract.2017.03.999
24. Takehira R, Murakami K, Katayama S, Nishizawa K, Yamamura S. A structural equation model (SEM) for pharmacist competencies in improving quality of life of cancer patients: effect of missing values on the SEM. *Pharmacol Pharm*. 2011;2:226-232. doi:10.4236/pp.2011.23031
25. Manfrin A, Apampa B, Parthasarathy P. A conceptual model for 'students' satisfaction with team-based learning using partial least squares structural equation modelling in a faculty of life sciences, in the United Kingdom. *J Educ Eval Health Prof*. 2019;16:36. doi:10.3352/jeehp.2019.16.36
26. Hannane A, Misane L, Devouassoux G, Colin C, Letrilliart L. Asthma 'patients' perception on their care pathway: a qualitative study. *NPJ Prim Care Respir Med*. 2019;29(1):9. doi:10.1038/s41533-019-0121-2
27. Hindi A, Parkhurst C, Rashidi Y, Ho SY, Patel N, Donyai P. Development and utilization of the Medicines Use Review patient satisfaction questionnaire. *Patient Prefer Adherence*. 2017;11:1797-1806. doi:10.2147/ppa.s146991
28. Krska J, Nesbit J, Baylie K, O'Kane A. Patient views on the MUR service. *Int J Pharm Pract*. 2009;17(supplment 1):A40-A42.
29. Bollen KA. Latent variables in psychology and the social sciences. *Annu Rev Psychol*. 2002;53(1):605-634.
30. Sarstedt M, Ringle C, Hair J. Partial least squares structural equation modeling. In: Homburg C, Klarmann M, Vomberg A, eds. *Handbook of Market Research*. Springer; 2017:1-40. doi:10.1007/978-3-319-05542-8_15-1
31. Calvo-Mora A, Leal A, Roldán JL. Relationships between the EFQM model criteria: a study in spanish universities. *Total Qual Manag Bus Excell*. 2005;16(6):741-770.
32. Hussain S, Fangwei Z, Siddiqi A, Ali Z, Shabbir M. Structural equation model for evaluating factors affecting quality of social infrastructure projects. *Sustainability*. 2018;10(5):1415. doi:10.3390/su10051415
33. Manfrin, A. & Krska, J. Consistency and replicability of a pharmacist-led intervention for asthma patients: Italian Medicines Use Review (I-MUR). *Prim Health Care Res Dev*. doi:10.1017/S1463423618000580
34. Sarstedt M, Hair JF, Ringle CM, Thiele KO, Gudergan SP. Estimation issues with PLS and CBSEM: where the bias lies! *J Bus Res*. 2016;69(10):3998-4010.
35. Ringle CM, Wende S, Becker JM. SmartPLS 3, *SmartPLS GmbH*. 2015. http://www.smartpls.com
36. Gudergan SP, Ringle CM, Wende S, Will A. Confirmatory tetrad analysis in PLS path modeling. *J Bus Res*. 2008;61(12):1238-1249.
37. Bollen KA, Ting K. A tetrad test for causal indicators. *Psychol Methods*. 2000;5(1):3-22.
38. Henseler J, Ringle C, Sinkovics R. The use of partial least squares path modeling in international marketing. *Adv Int Mark*. 2009;20:277-319. doi:10.1108/s1474-7979(2009)0000020014

39. Hair JF, Ringle CM, Sarstedt M. Partial least squares: the better approach to structural equation modeling. *Long Range Plann*. 2012c;45(5-6):312-319. doi:10.1016/j.lrp.2012.09.011
40. Sarstedt M, Ringle CM, Smith D, Reams R, Hair JF. Partial least squares structural equation modeling (PLS-SEM): a useful tool for family business researchers. *J Fam Bus Strategy*. 2014;5(1):105-115. doi:10.1016/j.jfbs.2014.01.002
41. Jöreskog KG. Simultaneous factor analysis in several populations. *Psychometrika*. 1971;36(4):409-426.
42. Tenenhaus M, Esposito Vinzi V, Chatelin YM, Lauro C. PLS path modeling. *Comput Stat Data Anal*. 2005;48(1):159-205.
43. Hair JF, Hult GTM, Ringle CM, Sarstedt M. *A Primer on Partial Least Squares StructuralEquation Modeling (PLS-SEM)*. 2nd ed. Sage; 2017.
44. Bagozzi RP, Yi Y. On the evaluation of structural equation models. *J Acad Mark Sci*. 1988;16(1):74-94.
45. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J Acad Mark Sci*. 2014;43(1):115-135. doi:10.1007/s11747-014-0403-8
46. Rigdon EE. Rethinking partial least squares path modeling: in praise of simple methods. *Long Range Plann*. 2012;45(5-6):341-358.
47. Shamueli G, Koppius OR. Predictive analytics in information systems research. *MIS Q*. 2011;35(3):553-572.
48. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. *Eur Bus Rev*. 2019;31(1):2-24. doi:10.1108/EBR-11-2018-0203
49. Cohen J. *Statistical Power Analysis for the Behavioral Sciences*. Lawrence Erlbaum Associates; 1988.
50. Shmueli G, Ray S, Velasquez Estrada JM, Chatla SB. The elephant in the room: predictive performance of PLS models. *J Bus Res*. 2016;69(10):4552-4564.
51. Krska J, Cromarty JA, Arris F, Jamieson D, Hansford D. Providing pharmaceutical care using a systematic approach. *Pharm J*. 2000;265:656-660.
52. The Scottish Office. Clinical pharmacy practice in primary care. *National Health Service in Scotland*. 1999. http://www.elib.scot.nhs.uk/portal/upload/Clin_Pharm_Pract_Prim_Care.pdf
53. Herborg H, Soendergaard B, Jorgenaen T, et al. Improving drug therapy for patients with asthma-part 2: use of antiasthma medications. *J Am Pharm Assoc*. 2001;41(4):551-559. doi:10.1016/s1086-5802(16)31279-7
54. Schulz M, Verheyen F, Mühlig S, et al. Pharmaceutical care services forasthma patients: a controlled intervention study. *J Clin Pharm*. 2001;41:668-676.
55. Wang X, Chen J, Burström B, Burström K. Exploring pathways to 'outpatients' satisfaction with health care in Chinese public hospitals in urban and rural areas using patient-reported experiences. *Int J Equity Health*. 2019;18(1):29. doi:10.1186/s12939-019-0932-3
56. Amankwah O, Weng-Wai C, Mohammed AH. Modelling the mediating effect of health care healing environment on core health care delivery and patient satisfaction in Ghana. *Environ Health Insights*. 2019;13:117863021985211. doi:10.1177/1178630219852115
57. Fahmi Khudair I, Asif Raza S. Measuring patients' satisfaction with pharmaceutical services at a public hospital in Qatar. *Int J Health Care Qual Assur*. 2013;26(5):398-419.
58. Sahin B, Yilmaz F, Lee KH. Factors affecting inpatient satisfaction: structural equation modeling. *J Med Syst*. 2006;31(1):9-16.
59. Hasan S, Sulieman H, Stewart K, Chapman CB, Hasan MY, Kong DCM. Assessing patient satisfaction with community pharmacy in the UAE using a newly-validated tool. *Res Social Adm Pharm*. 2013;9(6):841-850. doi:10.1016/j.sapharm.2012.10.002

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