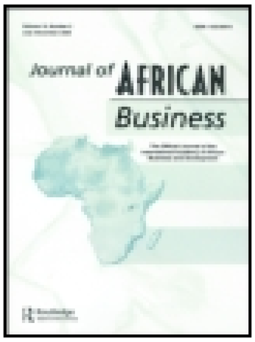

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Retention of Health Professionals in the Upper West Region of Ghana: Application of Partial Least Square Structural Equation Modelling

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ABSTRACT

This study aims at assessing the factors influencing the retention of health professional in the Upper West Region of Ghana. A self-administered questionnaire was used to collect data from 126 health professionals. Partial Least Square Structural Equation Modeling was used to estimate the relative effects of retention-influencing factors on retention decisions of health professionals. The study found that welfare benefits and working environment were determinants of health professionals' retention. The study recommends the provision of a good and safe working environment, improve living conditions and welfare benefits to make health professionals posts professionally attractive to increase retention of health workers.

KEYWORDS

Retention; health professional; structural equation modeling; Ghana

Introduction

The most significant resource that an organization possesses is its employees including their numbers, skill, and commitment which are crucial to the overall growth and success of the organization, and healthcare organizations are no exception. The healthcare organization goal of delivering good quality healthcare is positively associate with health professional numbers and quality. Efforts to scale up essential interventions to achieve the health-related targets of the Sustainable Development Goals (SDGs) and universal health coverage are likely to be defeated by insufficient numbers of adequately trained health workers in low- and middle-income countries (World Health Organisation, 2016).

World Health Organization (2016) estimates the shortage of health care workers to be approximately 17.4 million in 2013. In terms of regional distribution, the largest deficit of health workers was found in South-East Asia (6.9 million) followed by Africa (4.2 million). Even though the shortage is highest in South-East Asia in absolute terms mainly due to the region's large populations, in relative terms (i.e. taking into account population size) the African Region is the most challenged. The density of skilled health workers varies significantly across the world, for instance, from 106.4 per 10,000 population in the European

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Region to 14.1 per 10,000 population in the African Region (World Health Organization, 2016). The African figure is significantly low compared to the world median density of five per 1,000 people.

The shortage of health worker is further worsened by the severe imbalances in the distribution across and within countries. Around the world, there is a tendency for the health workers to be concentrated in affluent urban areas rather than in rural and poorer areas (Araújoa & Maedaa, 2013). World Health Organisation (2006) estimates that globally approximately one-half of the population lives in rural areas, but these areas are served by only 38% of the total nursing workforce and by less than 25% of the total physician workforce. For example, in Ghana, the number of public sector doctors, nurses and midwives per 1,000 of the population are 1.43 in urban Greater Accra and only 0.67 in the much more rural Northern Region (Ghebreyesus, Scheffler, & Soucat, 2013). The distribution of the health staff is largely skewed in favor of the two popular urban cities namely Accra and Kumasi. The Korle Bu and Komfo Anokye Teaching hospitals in Accra and Kumasi respectively employ more than 45% of the country's doctors while less than 15% are engaged by the district hospitals (Ghana Health Service, 2018).

Shortage of health workers remains a hindrance to quality health care delivery in the northern regions hence, creating uneven access to healthcare services. The situation in the Upper West Region is worse as critical staff (doctors, midwives and nurses) to population ratio continues to worsen. For instance, in 2017, the doctor-population ratio was 1:14,821, which was two times higher than the national average of 1:7,374 (Ghana Health Service, 2018). It was for this reason that Regional Minister, Alhaji Alhassan Sulemana lamented in a speech at the 60th-anniversary lecture of the Ghana Medical Association at Jirapa that most medical doctors refuse postings to the Region and that many of those who accept postings hardly stay for long (MyNewsGh.com 30 July, 2018).

Attraction and retention of health workers are critical for the total health system performance. For the Government of Ghana to achieve the health-related targets of the SDGs, universal health coverage and equity of access to quality preventive and curative health services, geographical variation in health personnel distribution need to be addressed particularly, in the underserved areas such as the Upper West Region.

Extant literature on the factors influencing retention of health care professionals are quite rich (see Adzei & Atinga 2012; Snow et al., 2011; Agyapong, Osei, Farren, & McAuliffe, 2015; Belaid, Dagenais, Moha, & Ridde, 2017; and Darkwa, Newman, Kawkab & Chowdhury, 2015). However, these studies are often limited to relying on descriptive and qualitative methods of investigation (see, for example, Belaid et al., 2017; and Darkwa et al. 2015). Some of these studies do the identification and classification of influential factors and their possible effect on retention. These research are conducted mostly through brainstorming, interviews, surveys, and experts' judgments. Two main flaws are associated with using this approach. First, merely listing of individual influential factors as if they are independent factors ignores possible interactions between them. Second, the approach measures the pairwise correlation between influential factors and the retention without looking at the multiple influencing effects. Analyzing the effect of individual factors, regardless of the multiple effects of several influential factors tends to underestimate the overall effects of retention. It is against this background that this study aims at filling this gap in the current body of literature by applying a structural model that describes the relationships between retention and retention-influencing factors. Therefore, the current study uses structural equation modeling to incorporate all the influencing factors (latent and observed variables) and retention into a structural model. The main objective of this study is to assess the factors influencing retention of health professional in the Upper West Region, Ghana.

The rest of the article is structured as follow: the next section reviews literature on factors influencing retention of health care professionals, and identifies the gaps that the study intends to fill. This is followed by developing a conceptual framework that describes the variables and hypothetical relationships of the proposed model. The next section describes the research methodology, including ethical considerations, study setting and data collection procedure. The results are then discussed, followed by a section on the conclusion and recommendations.

Literature review

Multiple factors influence a health worker decision to relocate, stay or leave a post in underserved areas. These factors are complex and interconnected and often connected to health professional's characteristics and preferences, related to health systems organization and wider social, political and economic environment (WHO, 2010). Although these factors are context-specific, the evidence from different countries suggests a common set of problems that differ in their mixture and degree of intensity (Araújoa & Maedaa, 2013). Frequently reported factors are: unsuitable pre-service training for rural and remote areas practice, lack of opportunities for further training and career development, low salaries, poor working environments, limited availability of equipment and drugs, insufficient family support, inadequate management and unsupportive supervision (Grobler et al., 2009). These factors have been described by other authors' as "pull" and "push" factors. The "pull" factors are those that attract health professionals to a given post/location (example, higher income or the possibility of practising in the private sector, improved working and living conditions etc.). The "push" factors are those that may coerce health workers not to take up a post in a remote location and not to remain there (Lehmann, Dieleman, & Martineau, 2008).

Henderson and Tulloch (2008) did an in-depth systematic review of the literature on incentives for retaining health workers in the Asia-Pacific region. The study categorized the incentives for retaining health workers into financial and non-financial. The authors stated that financial incentives are an important motivating factor for health workers, particularly in countries where government salaries and wages are insufficient in meeting the basic needs of health workers and their families. These incentives were identified to include higher salaries, salary supplements, benefits and allowances. On the other hand, the non-financial incentives were needed to provide a complete package to attract health workers to stay in rural and remote areas. These incentives include the broad categories of improved working and living conditions, continuing education, training and professional development, improved supervision and management, and gender-sensitive considerations. The findings of this study indicated that salaries and benefits, together with working conditions, supervision and management, and education and training opportunities, are important determinants of retention of health workers in the Asia-Pacific region. Hence, this review highlighted the importance of both financial and non-financial incentives.

Following Henderson and Tulloch (2008), Adzei and Atinga (2012) also categorized the factors influencing health worker motivation and retention into financial incentives and non-financial incentives. The financial incentives included salary supplements, benefits and allowances, whereas the non-financial incentives included improved working and living conditions, continuing education and professional development, supervision and management, among others. The two studies identified similar factors, therefore, making them reliable enough to be applied in analyzing incentives for health workers in the Ghanaian context.

A study conducted by Lehmann et al. (2008) reviewed the literature on attraction and retention of health workers in the remote rural areas in the middle- and low-income countries. The authors grouped the factors impacting on attraction and retention into five categories, namely individual factors, local environmental factors, work-related factors, national environment, and international environmental factors. Individual factors depend on personal characteristics such as gender, age, ethnicity, place of origin (rural or urban), personal values and beliefs among others which have a significant effect on a person's employment decision. Local environmental factors include the availability of good schools for children, safety and security, employment opportunities for spouse, good staff accommodation, and basic infrastructures such as the supply of good drinking water, electricity, quality housing, food markets, roads, transport and telecommunication. Work-related factors include pay or salary and conditions of service, "ability to generate income" which might include a second job, under-the-table payment or running a private practice in an urban area as a coping strategy to improve income levels. Several authors have identified working conditions which include organizational arrangements, management support, high-risk work environments and availability of equipment as a determining factor in health workers' decision to leave or stay in remote areas (Buchan & Calman, 2004; Dieleman, Cuong, Anh, & Martineau, 2003; Dieleman, Toonen, Toure, & Martineau, 2006). Other work-related factors include access to continuing education and professional advancement. A study by Awases, Gbary, Nyoni, and Chatora (2004) emphasized the importance of the perceived national environment as a factor influencing retention. This study, like that of Lehmann et al. (2008), revealed that social unrest and conflict rated high as a reason for emigration. Under international environment, elements that act as pull factors in attracting health staff to international destinations include higher remuneration, more satisfying working conditions, safer working environment and better educational and career development opportunities, as well as broader factors such as higher quality of life, freedom from political persecution, freedom of speech and educational opportunities for children.

Belaid et al. (2017) used the framework developed by Lehmann et al. (2008), which grouped the attraction and retention of health professionals influencing factors into five dimensions namely, the international, national, local, and work environments and individual factors. A mixed-method was employed to conduct the study in the Tillabery Region of Niger. While in-depth interviews, documentary review, and concept mapping were used to collect the data, a content analysis was conducted for the qualitative data. The results of this study revealed that local environment including living conditions (no electricity, lack of availability of schools), social factors (isolation, national and local insecurity), working conditions (workload), the lack of financial compensation, and individual factors (marital status, gender), were attraction and retention determined for health professionals in the rural areas.

Darkwa et al. (2015) conducted a qualitative study on factors influencing the retention of doctors and nurses at rural healthcare facilities in Bangladesh. In-depth interviews were conducted with healthcare providers (n = 15) and facility managers (n = 4) posted in rural areas, while key informant interviews were conducted with health policymakers at the national level (n = 2). Participants of this study reported of poor living conditions in rural areas (e.g., poor housing facilities and unsafe drinking water); overwhelming workloads with poor safety and insufficient equipment; and a lack of opportunities for career development, and skill enhancement. Participants further reported insufficient wages and inadequate opportunities for private practice in rural areas. Managers on their part reported of lack of sufficient authority to undertake disciplinary measures for absenteeism and the lack of fairness in promotion practices of providers. Finally, policymakers acknowledged the unavailability or insufficient allowances for rural postings and a lack of national policy on rural retention.

A qualitative study in Ghana by Snow et al. (2011) looked at key factors leading to reduced recruitment and retention of health professionals in remote areas and proposed policy solutions. The study carried out in-depth interviews with 84 doctors and medical leaders. All participants believed that rural postings must be accompanied by special career or monetary incentives as a result of a loss of locum (i.e. moonlighting income), higher workload, and professional isolation of remote assignments. Participants' common fears were career 'death' and prolonged rural appointments and suggested considerable career incentives such as a guaranteed promotion or a study opportunity after some fixed term of service in a remote or hardship area as policy solutions.

Even though many studies in the area of factors influencing retention of health care professionals have been done, a comprehensive study that encompasses all the significant influencing factors of retention has rarely been conducted in Ghana. Previous studies at best examine the correlation between the influencing factor and retention rather than exploring the effect that all the influencing factors work simultaneously on retention. To the best of the knowledge of these current authors no study has incorporated retention-influencing factors into a cohesive model. Thus, developing a model that incorporates the entire retention-influencing factors and retention to examine their relationships is necessary.

Conceptual framework and development of research hypotheses

Previous studies on factors influencing retention of health professionals provided the theoretical foundation for the development of a conceptual framework for this research model (see Adzei & Atinga, 2012; Agyapong et al., 2015; Belaid et al., 2017; Darkwa et al., 2015; and Snow et al., 2011). A critical review of the existing literature has resulted in categorizing the retention-influencing factors into seven dimensions. The study presumed that monetary compensation, working environment, training and development, welfare benefits, performance appraisal, disciplinary procedure, and career growth factors collectively impact retention of health care professionals in the Upper West Region, Ghana. However, the first dimension, monetary compensation, appears to be provided by most of the other dimensions which are content motivators. Based on aforementioned literature, the following six (6) hypotheses were developed and tested in this current study.

H1: Career growth will have a positive effect on employee retention.

H2: Disciplinary procedure will have a positive effect on employee retention.

H3: Performance appraisal will have a positive effect on employee retention.

H4: Training and development will have a positive effect on employee retention.

H5: Welfare benefits will have a positive effect on employee retention

H6: Good working environment will have a positive effect on employee retention.

The hypotheses stated above encompass a conceptual structural model and are viewed to be structural components of the SEM. The factors that influence retention are perceived to be highly subjective. Therefore, it is a complex matter to refine the right sort of attributes that measures the true representation of the latent factors (Aikin, Stein, & Bentler, 1994). Based on existing literature, the study formulated a comprehensive list of attributes which evidently characterize the seven latent factors of our model. The perceived effects of retention-influencing factors are as follows: five attributes of monetary compensation (MC1 to MC5), five attributes of career growth (CG1 to CG5), five attributes of disciplinary procedure (DP1 to DP5), five attributes of performance appraisal (PA1 to PA5), and five attributes of training and development (TD1 to TD5), four attributes of welfare benefits (WB1 to WB4) and six attributes of working environment (WE1 to WE6). The research model was tested using partial least squares-structural equation modeling (PLS-SEM) method by utilizing the SmartPLS 3.0 statistical software (Ringle, Wende, & Becker, 2015).

Research methodology

Ethical considerations

The study obtained ethical approval from the Department of Human Resource Management (SS/SHR/13/0033), University of Cape Coast–Ghana and Regional Health Administration (GHS/UWR/TP-51), Ghana Health Service, Upper West Region. All respondents were informed of the voluntary nature and their right to withdraw at any stage of participation. Confidentiality was assured, and respondents were not asked to identify themselves on the questionnaire, thereby ensuring anonymity. All returned questionnaires were locked in a room with only aggregate data reported.

Study setting

The Upper West Region is situated in the north-western part of the country, and is one of the sixteen regions of Ghana. The region has an estimated population of 702,110 inhabitants in 2010. Its predominant economic activity is agriculture. The region has the highest poverty incidence rate (i.e. 70.9%) in the country (Ghana Statistical Service, 2018).

According to the 2016 Annual Report (Upper West Regional Health Services, 2017), the region has a total of three hundred and thirty three (333) health facilities, providing various types of services. These health facilities include eleven (11) hospitals (government, private and Christian Health Association of Ghana), four (4) Polyclinics, seventy (70) health centers, fifteen (15) clinics, two hundred and twenty-seven (227) CHPS Compounds and five (5) maternity homes. In terms of human resources, there is one doctor to 16,222 population while nurse to population ratio stand at 1:597 in 2017 (Ministry of Health, 2018).

Research design, sample size, and sampling techniques

The study was approached quantitatively and applied descriptive research design. The population comprises healthcare professionals in the Upper West Region. The rationale for choosing the Upper West Region is based on popular knowledge that health professionals are difficult to attract and the few attracted rarely stay.

The determination of the sample size for this study is based on the formula for categorical data as presented by Bartlett, Kotrlik, and Higgins (2001). Using the proportion of 30% for health professionals who choose to work in underserved areas (Upper West Regional Health Services, 2011), degree of precision set at 8%, and Z-value of 1.96 for the 95% confidence level, we obtained a minimum sample size of 126.

Since the population of this study is geographically dispersed, and face-to-face contact was needed, the 126 health professionals were selected using a multistage sampling technique. The first stage involved the clustering of health professionals in the study area based on the 11 administrative districts in the region. Four districts (Wa Municipal, Wa East, Jirapa, and Nadowli-Kaleo) were randomly selected, and these constituted the target population. The selection of health professionals was based on the principle of selecting more persons from districts with more health professionals and vice-versa. A close look at the total health professionals in the region as provided by the Upper West Regional Health Directorate revealed that the distribution of health care professionals is uneven. Hence, health professionals included in the sample were selected proportionately to the total number of health personnel in a given district. Figures provided by the Regional Health Directorate formed the basis in the calculation of the total number of health professionals drawn from each selected district. Finally, a simple random sampling technique with the help of random function on the scientific calculator was used to select health professionals for the study.

Instrument development procedure/Preparation of questionnaire

The literature provided a guide to the construction of the questionnaire. A self-administered questionnaire was used to solicit information on the opinions of health professionals on retention. Health professionals ranked the influencing factors using a 5-point Likert scale (anchored at 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree). The basis of the questionnaire design was on the theory that at least three measurement variables reflect one latent variable to develop a stable structural equation model (Kline, 2011). The whole data collection exercise lasted for two months, from October and November 2018.

Structural equation modeling

Structural equation modeling (SEM) is a multivariate technique that combines multiple regression analysis and factor analysis to estimate simultaneously a series of interrelated dependence relationships (Hair, Anderson, Tatham, & Black, 1998). This technique was developed from econometric modeling of multiple equation systems. It has been used extensively in the area of psychology, biological sciences, educational research, economics, and business disciplines such as management, marketing, information technology and finance among others (Abugre, 2019; Makanyeza, Macheyo, & Toit, 2016; Qureshi & Kang, 2015 etc.). The popularity of SEM is based on its use of confirmatory methods which provide a comprehensive means for assessing and modifying theoretical models for researchers. Hence, SEM offers great potential for furthering the development of theories.

A number of advantages are associated with the use of SEM for data analysis as opposed to alternative multivariate techniques such as regression or multivariate analysis of variance. First, SEM allows the results of relationships between constructs not only unbiased by measurement error but also equivalent to relationships between variables of perfect reliability (Werner & Schermelleh-Engel, 2009). Second, SEM allows researchers to examine complex patterns of relationships such as the focus of this study. Finally, SEM allows researchers to use several indicator variables per construct simultaneously, leading to more valid conclusions on the construct level (Werner & Schermelleh-Engel, 2009). The rationale for using SEM in this study is that it allows a broad range of factors affecting retention of health professionals to be addressed simultaneously.

A SEM model has two parts, a measurement model and a structural model. The measurement model is to evaluate the unobserved latent variables or constructs as linear functions of observed variables, and the structural model is to examine the direction and strength of the relationships of the latent variables that is endogenous and exogenous (Qureshi & Kang, 2015; Washington, 2011). The measurement model can be defined with the following equations:

$$y_{ij} = \lambda_{ij}\eta_j + \omega_{ij} \tag{1}$$

$$x_{kl} = \delta_{kl}\xi_l + \varepsilon_{kl} \tag{2}$$

where y_{ij} indicates the i observed indicator of the j latent construct, λ_{ij} is the correlation coefficient between y_{ij} and η_j, η_j denotes the j latent construct, x_{kl} is the k observed indicator of the l latent construct, δ_{kl} is the correlation coefficient between x_{kl} and ξ_l, ξ_l denotes the l latent construct, and ω_{ij} and ε_{kl} are error terms. In this study, retention is considered as endogenous latent construct measured by using Equation (1) with measurement indicators RE3, RE4, and RE5, while the retention-influencing factors are regarded as exogenous latent constructs measured by using Equation (2) with corresponding measurement indicators.

The basic equations of the structural model can be expressed as follows:

$$\eta = B\eta + \Gamma\xi + \epsilon \tag{3}$$

where η is the endogenous variable, ξ is the exogenous variable, B indicates the interactions between endogenous variables, Γ is the coefficient matrix expressing the impacts of the exogenous variables on the endogenous variables, and ϵ represents the error term.

Often a two-step analysis is used to develop a structural model (Byrne, 2010). The first step involves the performance of a confirmatory factor analysis (CFA) to test the reliability and validity of the measurement variables and to provide a basis for a later structural analysis. The second step is where the SEM is applied to test the hypothesis or to explore the causal relationships between latent constructs. The overall fit of the model is explored based on various goodness-of-fit indices. Also, the paths with nonsignificant correlation coefficient should be removed to refine the structural model (Zhao, Wang, Mbachu, & Liu, 2019).

Results and discussion

Measurement model assessment

The dataset was examined with the view to ascertain whether measurement model requirement criteria were met to check for suitability for further analysis. The first step in assessing the measurement model involved examining the indicator loadings. All measurement items which did not meet the minimum acceptable loading of 0.50 (Kim, Kim, & Wachter, 2013) were dropped (See Figure A1 for removed measurement indicators that were not part of the final model). Meeting the minimum acceptable loading criteria indicate that the construct explains at least 50% of the indicator's variance, thus providing acceptable item reliability. Elimination of some constructs reduced the number of items to a manageable size for the analysis. Observation revealed that monetary compensation indicators have a weak factor loading, as all of the constructs were statistically insignificant. Thus, excluding monetary compensation, six latent variables were finally retained. Additionally, deleted indicators were two attributes from retention (RE1 & RE2). The final research model for the study was obtained after eliminating nonsignificant paths and this was done to ensure best fit. Figure 1 gives a snapshot of latent variables used for the present study.

The Cronbach's alpha (CA) and the Composite Reliability (CR) statistics were used to assess the internal consistency reliability. Empirically, for a good and reliable instrument, the coefficients of Cronbach's alpha and composite reliability should always be higher than 0.7 (Nunnally, 1967). Results, as shown in Table 1, revealed that all the coefficients of the Cronbach's alpha and Composite Reliability were above the recommended threshold of 0.70, which means that the responses strongly hang together. Thus, the items in this study have sufficient internal consistency (Nunnally, 1967). Average Variance Explained (AVE) for all items on each construct was used to evaluate the constructs convergent validity. Convergent validity measures the extent to which the construct converges to explain the variance of its items (Hair, Risher, Sarstedt, & Ringle, 2018). The finding shows that all of the AVE values meet the minimum acceptable threshold of 0.5, confirming convergent validity (Hair et al., 2018).

Three criteria namely Fornell and Larcker's criterion, cross-loading and Heterotrait-Monotrait Ratio (HTMT) were used to assess discriminant validity. The Fornell-Larcker criterion suggests that the square root of the AVE of each construct should be higher than its highest correlation with any other construct (Fornell & Larcker, 1981). The results as displayed in Table 2 revealed that all square root of AVE ranged between 0.671 and 0.864 exceeded the inter-construct correlations; therefore, discriminant validity is satisfied.

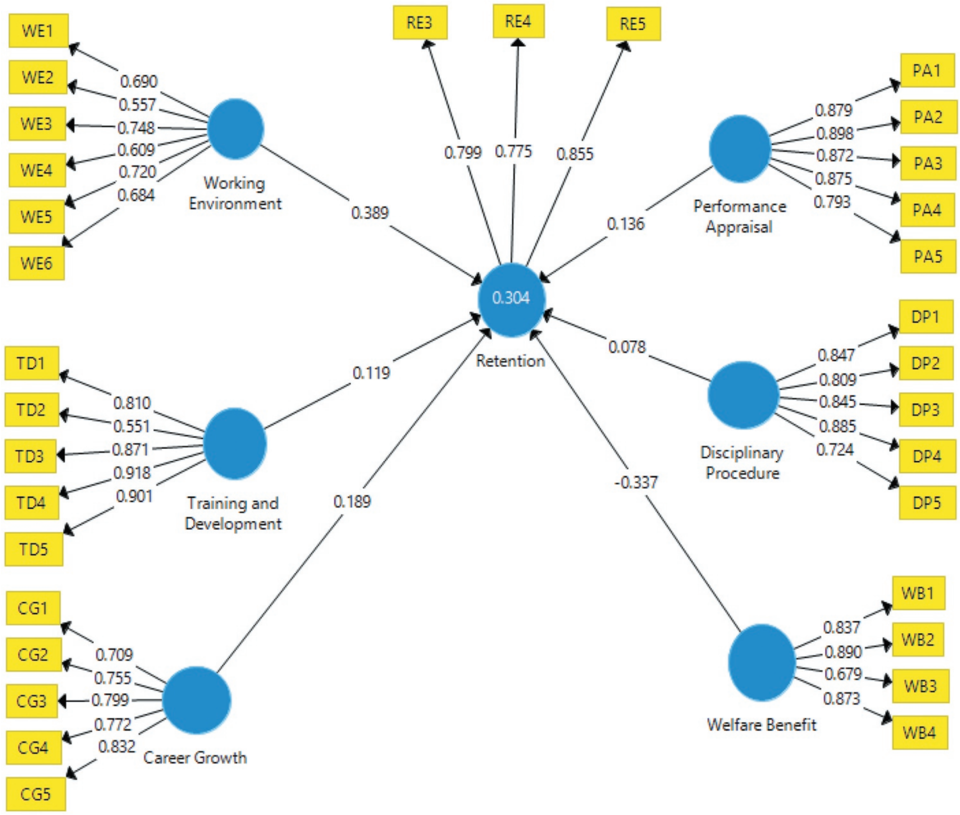

Figure 1. PLS Path Model Estimation.

The second criterion for evaluating discriminant validity is cross-loading assessment. As suggested by Hair, Hult, Ringle, and Sarstedt (2017), the loading of a certain variable must load higher than the cross-loading of other variables. It is observed that all loadings of the measurement items were higher than any other cross-loadings, indicating that discriminant validity of the model has been attained (see Table A1).

Henseler, Ringle, and Sarstedt (2015) indicated that the Fornell-Larcker criterion and cross-loading approaches cannot reliably detect the lack of discriminant validity in most research scenarios. The authors proposed an alternative method called Heterotrait-monotrait ratio of correlations (HTMT) which is based on the multitrait-multimethod matrix. As the robustness check for discriminant validity the study employed the HTMT. The HTMT measures correlations within latent variables to correlations between the variables. To achieve the discriminant validity under the HTMT approach the cutoff value must be below 0.85 (Kline, 2011). The results from Table 3 show that all values are less than the recommended threshold of 0.85. Additionally, the confidence interval of each HTMT value does not include the value 1 for all combinations of constructs, thus showing that discriminant validity is established.

Table 1. Validity and Reliability Analysis of the Measures.

Constructs/Measures	Loadings	(t-values)
Career growth (CA = 0.837; ρ_A = 0.861; CR = 0.882; AVE = 0.600)		
CG1: GHS supporting staff career growth on merit and experience	0.709	8.921
CG2: The career path for individuals is clearly defined at GHS	0.755	9.665
CG3: Promotions based on merit and experience	0.799	18.013
CG4: Retention influenced by staff mentorship and coaching programs	0.772	15.488
CG5: Succession planning practice	0.832	14.612
Disciplinary procedure (CA = 0.884; ρ_A = 0.903; CR = 0.913; AVE = 0.679)		
DP1: Fair and just disciplinary procedure in the region	0.847	20.392
DP2: Supervisors at GHS correcting staff at fault humanely	0.809	19.325
DP3: Disciplinary rules and regulations are clearly communicated to staff	0.845	20.508
DP4: Appeals are allowed on disciplinary decisions	0.885	33.735
DP5: Disciplinary actions being applied to all without favor	0.724	7.787
Performance appraisal (CA = 0.916; ρ_A = 0.931; CR = 0.937; AVE = 0.747)		
PA1: Performance targets being clearly stated	0.879	32.706
PA2: Performance targets being set with my supervisor	0.898	38.681
PA3: Performance ratings being done fairly	0.872	26.582
PA4: The performance appraisal review period is sufficient	0.875	33.035
PA5: Performance appraisal results used for career growth	0.793	14.873
Training & development (CA = 0.884; ρ_A = 0.939; CR = 0.910; AVE = 0.675)		
TD1: GHS supports for staff training and development	0.810	13.533
TD2: Training opportunities allocated fairly	0.551	3.906
DP3: Disciplinary rules and regulations are clearly communicated to staff	0.871	19.087
DP4: Appeals are allowed on disciplinary decisions	0.918	36.784
TD5: Training and development based promotions at GHS	0.901	36.017
Welfare benefit (CA = 0.846; ρ_A = 0.893; CR = 0.893; AVE = 0.679)		
WB1: Leave administration policy is influencing retention in the region	0.837	3.166
WB2: GHS cares for its employee's general welfare	0.890	3.325
WB3: Recreational facilities provided to staff at GHS	0.679	3.339
WB4: GHS education policy for staff and dependants	0.873	3.413
Working environment (CA = 0.753; ρ_A = 0.760; CR = 0.830; AVE = 0.451)		
WE1: GHS provides adequate modern equipment	0.683	8.525
WE2: Influenced by light workload and no burnout	0.557	4.921
WE3: Proper infrastructure (like electricity, water, good roads, etc.)	0.748	13.869
WE4: Higher social recognition in the region, with more associated gifts	0.609	5.637
WE5: Good working relationship with my colleagues	0.720	10.156
WE6: Good working relationship with my superiors	0.684	8.127
Retention (CA = 0.740; ρ_A = 0.749; CR = 0.852; AVE = 0.657)		
RE3: I love my job in the region	0.799	16.037
RE4: I am hoping to retire in the region	0.775	13.607
RE5: I will recommend the region to people in other regions	0.855	23.252

Notes: CA = Cronbach's Alpha; ρ_A = rho_A; CR = Composite Reliability; AVE = Average Variance Extracted; all loadings were significance at 1%

Table 2. Discriminant Validity (Fornell-larcker Criterion).

Latent variables	CG	DP	AP	RE	TD	WB	WE
Career growth (CG)	**0.774**						
Disciplinary procedure (DP)	0.726	**0.824**					
Performance appraisal (PA)	0.728	0.680	**0.864**				
Retention (RE)	0.372	0.389	0.386	**0.811**			
Training & development (TD)	0.530	0.446	0.543	0.323	**0.821**		
Welfare Benefit (WB)	0.555	0.451	0.537	0.172	0.649	**0.824**	
Working environment (WE)	0.388	0.461	0.450	0.436	0.550	0.561	**0.671**

Note: Value in the diagonals cell (**bold**) represents the square root of AVE

Structural model and hypothesis testing

According to Byrne (2010), collinearity suggests the presence of a strong correlation between variables representing the same underlying construct. An endeavor was made to

Table 3. Values and Confidence Intervals for HTMT.

Constructs	HTMT values	Confidence Interval 2.5%	97.5%
Disciplinary Procedure -> Career Growth	0.842	0.727	0.944
Performance Appraisal -> Career Growth	0.811	0.708	0.903
Performance Appraisal -> Disciplinary Procedure	0.733	0.563	0.875
Retention -> Career Growth	0.433	0.256	0.606
Retention -> Disciplinary Procedure	0.447	0.290	0.619
Retention -> Performance Appraisal	0.447	0.268	0.609
Training and Development -> Career Growth_	0.609	0.452	0.755
Training and Development -> Disciplinary Procedure	0.531	0.338	0.685
Training and Development -> Performance Appraisal	0.598	0.418	0.733
Training and Development -> Retention	0.329	0.216	0.534
Welfare Benefit -> Career Growth	0.663	0.526	0.803
Welfare Benefit -> Disciplinary Procedure	0.547	0.375	0.704
Welfare Benefit – > Performance Appraisal	0.590	0.418	0.741
Welfare Benefit -> Retention	0.243	0.159	0.431
Welfare Benefit -> Training and Development	0.760	0.638	0.878
Working Environment -> Career Growth	0.485	0.318	0.695
Working Environment -> Disciplinary Procedure	0.564	0.359	0.758
Working Environment -> Performance Appraisal	0.529	0.365	0.705
Working Environment -> Retention	0.571	0.401	0.754
Working Environment -> Training and Development	0.673	0.536	0.814
Working Environment -> Welfare Benefit	0.680	0.565	0.809

check whether the dataset suffered from the problem of collinearity or not. The study used the Variance Inflation Factor (VIF) in this regard. VIF values greater than 5 indicate the presence of collinearity problem (Garson, 2016). The results revealed that the highest outer VIF value was 3.664, falling within the acceptable range (see Table A2).

Results as shown in Table 4 indicate acceptable fit indices. The reported results are from estimated model, which is based on a total effect scheme and takes the model structure into account. Generally, it is shown that the items of each construct fit well; as all the fit statistics were relatively strong. For instance, the Standardized Root Mean Square Residual (SRMR) value of 0.089 indicates that the observed correlation and the model implied correlation matrix are well fitted. SRMR indicates acceptable fit when it produces a value smaller than 0.10 (Hu & Bentler, 1999). The same conclusions could be made for the Normed Fit Index (NFI) value. Conventionally, NFI values fall between 0 and 1, the closer the value to 1, the better the fit. The NFI value of 0.661 in this study is an indication the model has a good fit and as such construct validity has been achieved. Therefore, it is concluded that each item measures exactly what it was supposed to have measured.

To determine the statistical significance of the path coefficients, the bootstrapping method was used. The relationships between the constructs assisted in testing the proposed hypotheses. The path coefficient and it corresponding t-value was used to test each of our null hypotheses. The results for the structure model are shown in Table 5 and Figure 2. The results revealed that of the six latent variables only two were statistically

Table 4. Goodness-of-Fit Indices for the Structural Equation Model.

Fit indices	Estimated Model
SRMR	0.086
Chi-Square	1,005.347
NFI	0.672

significant (i.e. welfare benefit and working environment) in influencing health professional retention. The results show that there is a significant and negative relationship between welfare benefit and retention of health professional ($\beta = -0.337$, $p < 0.01$). According to Torrington and Hall (1998), employee welfare is intended to make life worth living for workmen. On the contrary, the latent variable welfare benefit is a significant negative determinant of employee retention in this study. The negative coefficient indicates that current welfare policy being practised by Ghana Health Service (GHS) encourages health professional to leave the region. A plausible explanation for this

Table 5. Path Coefficients and Hypothesis Testing.

Relationship	Path Coefficients	Standard Deviation	T Statistics (Bootstrap)	P-Values	Decision
Career Growth -> Retention (H1)	0.189	0.152	1.244	0.214	Rejected
Disciplinary Procedure -> Retention (H2)	0.078	0.132	0.594	0.553	Rejected
Performance Appraisal -> Retention (H3)	0.136	0.147	0.926	0.355	Rejected
Training and Development -> Retention (H4)	0.119	0.118	1.004	0.316	Rejected
Welfare Benefit -> Retention (H5)	−0.337	0.126	2.684	0.008	Accepted
Working Environment -> Retention (H6)	0.389	0.101	3.841	0.000	Accepted

R-square = 0.308
*** $p < 0.01$.

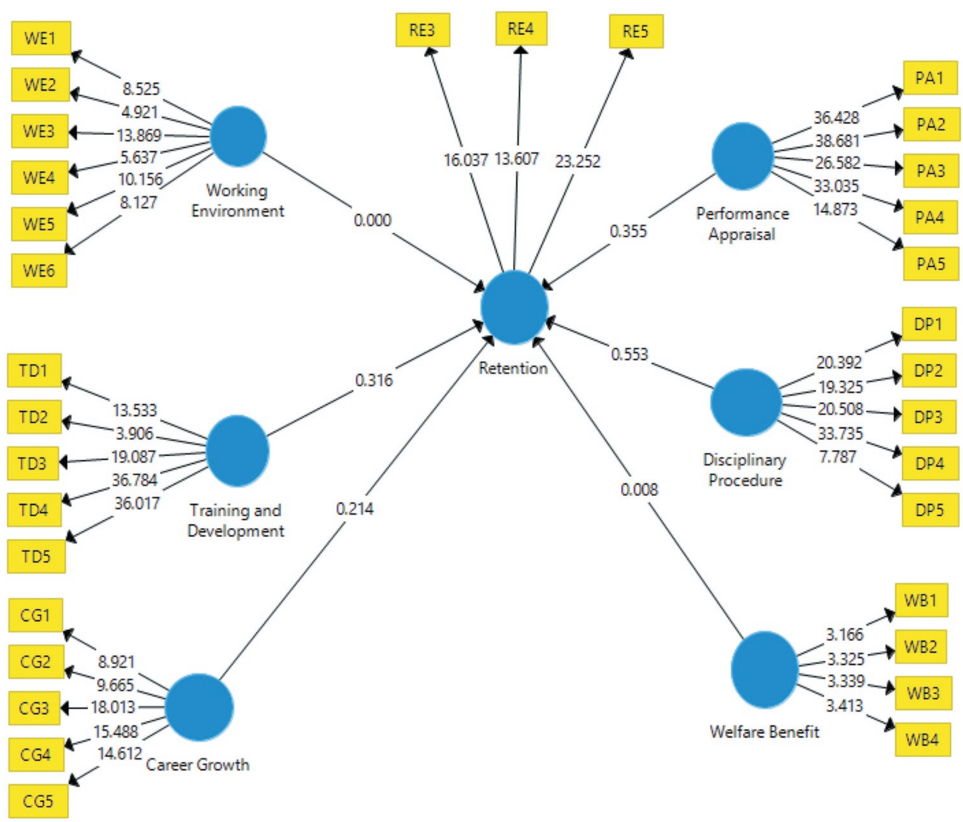

Figure 2. Structural Model of the Study.

finding is that the GHS might not have effective leave policy, recreational facilities and educational policy for staff and their dependants hence, leading to poor retention.

The latent variable working environment is a positive determinant of employee retention and this was significant at 1% (β = 0.389, $p < p < 0.01$). This result supports the hypothesis that good working environments have a positive effect on employee retention. The implication of the positive effect of working environment on retention is that health professional in the region believed that their retention is being influenced by factors such as provision of modern equipment, light workload and no burnout, proper infrastructure (like electricity, water, good roads, transport, and access to ICT) among others. Intuitively, an improved working environment is naturally expected to motivate workers by providing the needed serene environment for efficient work and therefore improve retention. This result is consistent with the available literature, which has documented that the working environment influences retention of health professionals (Darkwa et al., 2015; Belaid et al., 2017; Henderson & Tulloch, 2008).

Assessment of the coefficient of determination (R^2) is a major part of evaluating the structural model. As suggested by Chin (2010), R^2 values of 0.67, 0.33, and 0.19 are considered substantial, moderate, and weak, respectively. The R^2 of the endogenous latent variable in the current study is considered moderate and acceptable. From Table 5, the R^2 value (0.304) as also shown in Figure 1, implies that the six exogenous latent variable can jointly explain 30.4% of the variance of the endogenous construct retention.

In addition to assessing the R^2 value, the study also evaluated the effect size (f^2). The f^2 measures the effect of a particular exogenous latent variable on endogenous latent variable through the means of changes in the R^2 (Chin, 1998). According to Cohen (1988), f^2 value of 0.02, 0.15, and 0.35 are interpreted as a small, medium, and large effect sizes, respectively. Table 6 shows the results of the effect size of each latent variables. Interestingly, welfare benefit and working environment had a medium effect size in the model with f^2 value of 0.076 and 0.126, respectively. By Cohen (1988) suggestion, career growth (0.017), disciplinary procedure (0.004), performance appraisal (0.010), training and development (0.010) did not influence retention.

To assess the PLS path model's predictive accuracy is to calculate the Q^2 value (Geisser, 1974; Stone, 1974). As a rule of thumb, Q2 value greater than 0 (zero) indicates that the exogenous variables have predictive relevance on the particular endogenous variable, while Q2 less than zero show that there is no predictive relevance (Chin, 1998). After using the blindfolding technique with an omission distance of $D = 8$, the study obtains a positive Stone-Geisser's Q^2 value of 0.16, indicating evidence of predictive relevance in our model (see Table 7).

The interpretation of the R^2 statistic as a measure of model's predictive power is not entirely correct since it only indicates in-sample explanatory power and says nothing

Table 6. Effect Sizes on Exogenous Constructs.

Exogenous Constructs	f^2	Effect Size
Career Growth	0.017	Small
Disciplinary Procedure	0.004	Small
Performance Appraisal	0.010	Small
Training and Development	0.010	Small
Welfare Benefit	0.076	Medium
Working Environment	0.126	Medium

Table 7. Construct *Cross-Validated Redundancy*.

Total	SSO	SSE	Q2 (=1-SSE/SSO)
Retention	378.00	315.91	0.16

Table 8. Predictive Performance of the PLS Model versus Benchmark LM.

	PLS Predict			LM Predict		
Endogenous Construct	RMSE	MAE	Q2_predict	RMSE	MAE	Q2_predict
RE5	1.319	1.119	0.147	1.476	1.160	−0.068
RE3	1.131	0.958	0.167	1.269	1.034	−0.049
RE4	1.299	1.053	0.088	1.555	1.264	−0.307

about the out-of-sample predictive power of a model (Dolce, Esposito, & Lauro, 2017; Shmueli & Koppius, 2011). To address this concern, Shmueli, Ray, Estrada, and Chatla (2016) suggested a set of procedures for out-of-sample prediction referred to as a holdout sample. In standard PLS-SEM software such as SmartPLS, the PLSpredict procedure generates the holdout sample-based predictions (Ringle et al., 2015). Shmueli et al. (2019) argued that PLSpredict offers a way to evaluate a model's out-of-sample predictive power (i.e. a model's accuracy when predicting the outcome value of new cases).

In using PLSpredict to assess the model predictive power, first, the study evaluated whether the PLS path model predictions outperform the most naïve benchmark. Results from Table 8 revealed positive Q^2 predict values, indicating that the PLS path model prediction errors are smaller than the prediction errors given by the naïve benchmark. Second, the study compared the root mean square error (RMSE) and mean absolute error (MAE) values of the PLS path model with a naïve benchmark. The naïve benchmark uses a linear regression model (LM) to generate predictions for the manifest variables by running a linear regression of each of the dependent construct's indicators on the indicators of the exogenous latent variables in the PLS path model (Evermann & Tate, 2016). The results show that all indicators in the PLS-SEM analysis have lower RMSE and MAE values compared to the naïve LM benchmark, providing evidence that our model has high predictive power (Shmueli et al., 2019).

Conclusion and recommendations

The study sought to test the effects of retention-influencing factors or dimensions on retention decisions of health professional in the Upper West Region, Ghana. The research findings of this study have some implications on theory, policy and practice, and future research.

The study has established how factors of different categories can be combined in a model and how structural equation modeling can be utilized to analyze underlying relationships between retention and its influencing factors. Of the six dimensions of retention, only two were found to have a significant effect on retention decisions of health professional in the study area. The study established that working environment has a positive effect on retention. This means that health professionals believed that their retention in the region is being influenced by factors such as the provision of modern equipment, light workload and no burnout, proper infrastructure (like electricity, water, good roads, transport, and access to ICT) among others. Therefore, conducive working environment, if provided by GHS, will be able to motivate health workers to stay in the region. The study further revealed that welfare benefit is a negative determinant of employee retention, establishing that inadequate welfare benefits are one of the major reasons why health professionals do not want to stay in the region. By implication, current welfare policy of Ghana Health Service does not encourage retention of health professional in the region. The results have further revealed that although various studies have established that career growth; training and development; disciplinary procedure; and performance appraisal do influence retention of health professionals, these are not the case in the Upper West Region of Ghana.

Based on the results found, the study made the following recommendations. First, recognizing that working environment is a positive determinant of employee retention, the Ministry of Health through it agency, the Ghana Health Service, should continuously provide a good and safe working environment (including provision of appropriate/modern equipment and supplies, supportive supervision and mentoring) in the Upper West Region in order to make health professionals posts professionally attractive, thereby increase attraction and retention of health workers into the region. For instance, during the outbreak of the Covid-19 pandemic, there were cries of inadequate supplies of the appropriate personal protective equipment (PPEs). These, the government should provide not only to make working in the Region attractive but also to make it safe.

Second, the Government should also improve living conditions of health workers and their families by investing in infrastructure and services (such as sanitation, electricity, telecommunications, schools, portable water, etc.), as these factors have a significant influence on a health professional's decision to locate to and remain in the region. Finally, since welfare benefits affect retention negatively, proper welfare benefits should be provided by GHS. A welfare package may include proper leave policy, recreational facilities, housing units, transport facilities, canteens services and other cash benefits, as these would go a long way to improve retention of health professional in the region. It is suggested that much as these welfare elements are to be provided to retain health professionals, the professionals should also be retained in order to be provided these. This means specific benefits should be provided after a given number of years' service so that professionals do not take undue advantage of benefits and then leave. If this is not done, the purpose of retaining health professionals is likely to be defeated.

Limitations and direction for future research

Despite the overwhelming importance of this study to management and theory, it has a methodological limitation. This limitation is in the area of usage of the sample size and cross-sectional survey. Even though the current sample size seems adequate for a single quantitative study, the study is restricted to the Upper West Region, and this might limit the extent of generalization of the findings to other underserved areas. The study suggests that future research should use an alternative method of data collection such as panel dataset, or even increase the sample size. In this instance, a longitudinal investigation is highly recommended for a better understanding of the change and continuity with the relationship between retention-influencing factors and retention decisions of health professional over time.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Abugre, J. B. (2019). The moderating role of affective interpersonal conflict on managerial decision-making and organizational performance in private sector organizations: A study of Ghana. *Journal of African Business*. Advance online publication. doi: 10.1080/15228916.2019.1596707

Adzei, F. A., & Atinga, R. A. (2012). Motivation and retention of health workers in Ghana's district hospitals: Addressing the critical issues. *Journal of Health Organization and Management*, *26*(4), 467–485.

Agyapong, V. I. O., Osei, A., Farren, C. K., & McAuliffe, E. (2015). Factors influencing the career choice and retention of community mental health workers in Ghana. *Human Resources for Health*, *13*(56). doi:10.1186/s12960-015-0050-2

Aikin, L. S., Stein, J. A., & Bentler, P. M. (1994). Structural equation analysis of clinical sub-population differences and comparative treatment outcomes: Characterizing the daily lives of drug addicts. *Journal of Consulting and Clinical Psychology*, *62*(3), 488–499.

Araújoa, E. C., & Maedaa, A. (2013). *How to recruit and retain health workers in rural and remote areas in developing countries: A guidance note. Health Nutrition and Population (HNP) Discussion Paper No. 78506*. Washington, DC: World Bank.

Awases, A., Gbary, A., Nyoni, J., & Chatora, R. (2004). *Migration of health professionals in six countries: A synthesis report*. Brazzaville: World Health Organization. Retrieved from http://indexmedicus.afro.who.int/iah/fulltext/migrat_eng.pdf

Bartlett, J. E., Kotrlik, J. W., & Higgins, C. C. (2001). Organizational research: Determining appropriate sample size in survey research. *Learning and Performance Journal*, *19*, 43–50.

Belaid, L., Dagenais, C., Moha, M., & Ridde, V. (2017). Understanding the factors affecting the attraction and retention of health professionals in rural and remote areas: A mixed-method study in Niger. *Human Resources for Health*, *15*, 60.

Buchan, J., & Calman, L. (2004). *The global shortage of registered nurses: An overview of issues and actions*. Geneva: International Council of Nurses.

Byrne, B. M. (2010). *Structural equation modelling with AMOS: Basic concepts, applications, and programming*. Abingdon: Routledge.

Chin, W. W. (1998). The partial least squares approach to structural equation modelling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336).New Jersey: Lawrence Erlbaum Associates Publisher.

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares: Concepts, methods and applications* (pp. 655–690). Springer: Berlin/Heidelberg, Germany.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Darkwa, E. K., Newman, M. S., Kawkab, M., & Chowdhury, M. E. (2015). A qualitative study of factors influencing retention of doctors and nurses at rural healthcare facilities in Bangladesh. BMC Health Services Research, *15(1)*,1–12. doi:10.1186/s12913-015-1012-z.

Dieleman, M., Cuong, P. V., Anh, L. V., & Martineau, T. (2003). Identifying factors for job motivation of rural health workers in North Vietnam. *Human Resources for Health*, *1*(1), 10.

Dieleman, M., Toonen, J., Toure, H., & Martineau, T. (2006). The match between motivation and performance management of health sector workers in Mali. *Human Resources for Health*, *4*(2). Retrieved from https://human-resources-health.biomedcentral.com/articles/10.1186/1478-4491-4-2

Dolce, P., Esposito, V. V., & Lauro, C. (2017). Predictive path modelling through pls and other component-based approaches: Methodological issues and performance evaluation. In H. Latan & R. Noonan (Eds.), *Partial least squares path modelling: Basic concepts, methodological issues and applications* (pp. 153–172). Cham: Springer International Publishing.

Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators". *Journal of Business Research*, *69*(10), 4565–4582.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Garson, G. D. (2016). *Partial least squares regression and structural equation models*. Asheboro: Statistical Associates.

Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika*, *61*(1), 101–107.

Ghana Health Service. (2018). *The health sector in Ghana: Facts and figures 2018*. Accra: Author.

Ghana Statistical Service. 2018. *Ghana living standards survey round 7 (GLSS7)* (pp. 18-26)**.** Accra: Author. Retrieved from http://www2.statsghana.gov.gh/docfiles/publications/GLSS7/Poverty%20Profile%20Report_2005%20-%202017.pdf

Ghebreyesus, T. T., Scheffler, R. M., & Soucat, A. L. B. (2013). *Labour market for health workers in Africa: New look at the crisis*. Washington DC: World Bank.

Grobler, L., Marai, B. J., Mabunda, S. A., Marindi, P. N., Reuter, H., & Volmink, J. (2009). Interventions for increasing the proportion of health professionals practising in rural and other underserved areas. *Cochrane Database of Systematic Reviews*, (1), CD005314. doi:10.1002/14651858.CD005314.pub2

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modelling (PLS-SEM)* (2nd ed.). London: Sage Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2018). When to use and how to report the results of PLS-SEM. *European Business Review*. doi:10.1108/EBR-11-2018-0203

Hair, J. R., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). New Jersey: Prentice Hall International Inc.

Henderson, L. N., & Tulloch, J. (2008). Incentives for retaining and motivating health workers in Pacific and Asian countries. *Human Resources for Health*, *6*(18). Retrieved from https://human-resources-health.biomedcentral.com/articles/10.1186/1478-4491-6-18

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Hu, L., & Bentler, P. M. (1999). Fit indices in covariance structure modelling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, *3*(4), 424–453.

Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, *56*, 361–370.

Kline, R. B. (2011). *Principles and practice of structural equation modelling* (3rd ed.). New York: The Guilford Press.

Lehmann, U., Dieleman, M., & Martineau, T. (2008). Staffing remote rural areas in middle- and low-income countries: A literature review of attraction and retention. *BMC Health Services Research*, *8*, 19.

Makanyeza, C., Macheyo, R., & Toit, D. F. (2016). Perceived product necessity, perceived value, customer satisfaction and affective attitude: An integrative model. *Journal of African Business*, *17*(1), 69–86.

Ministry of Health. (2018). *Holistic assessment of 2017 health sector programme of work*. Accra: Author.

MyNewsGh.com. (2018, July 30). U/W: Doctor-Patient ratio affecting lives. Retrieved from https://mynewsgh.com/u-w-doctor-patient-ratio-affecting-lives-minister/

Nunnally, J. C. (1967). *Psychometric theory*. New York: McGraw Hill.
Qureshi, S. M., & Kang, C. (2015). Analysing the organizational factors of project complexity using structural equation modelling. *International Journal of Project Management*, *33*(1), 165–176.
Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS3*. SmartPLSGmbH: Boenningstedt.
Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly*, *35*(3), 553–572.
Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552–4564.
Shmueli, G., Sarstedt, M., Cheah, J., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347.
Snow, R. C., Asabir, K., Mutumba, M., Koomson, E., Gyan, K., Dzodzomenyo, M., . . . Kwansah, J. (2011). Key factors leading to reduced recruitment and retention of health professionals in remote areas of Ghana: A qualitative study and proposed policy solutions. *Human Resources for Health*, *9*(13). Retrieved from https://human-resources-health.biomedcentral.com/articles/10.1186/1478-4491-9-13
Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society*, *36*(2), 111–147.
Torrington, D., & Hall, L. (1998). *Human resource management*. Harlow: Pearson Education Limited.
Upper West Regional Health Services. (2011). Annual report. Retrieved from http://www.ghanahealthservice.org/rhditems.php?ghs&ghsscid=31&ghsrid=3
Upper West Regional Health Services. (2017). *2016 Annual Report*. Accra: Ghana Health Services. Retrieved from https://www.ghanahealthservice.org/downloads/2016_UWR_Annual_Report.pdf
Washington, S. (2011). *Statistical and econometric methods for transportation data analysis*. Boca Raton: Chapman and Hall/CRC.
Werner, C., & Schermelleh-Engel, K. (2009). *Introduction to structural equation modelling LISREL*. Frankfurt: Goethe University.
World Health Organisation. (2006). *The world health report 2006-working together for health*. Geneva: Author.
World Health Organisation. (2010). *Increasing access to health workers in remote and rural areas through improved retention: Global policy recommendations*. Geneva: Author.
Zhao, L., Wang, B., Mbachu, J., & Liu, Z. (2019). New Zealand building project cost and its influential factors: A structural equation modelling approach. *Advances in Civil Engineering*. Article ID 1362730, 15. doi:10.1155/2019/1362730

Appendix

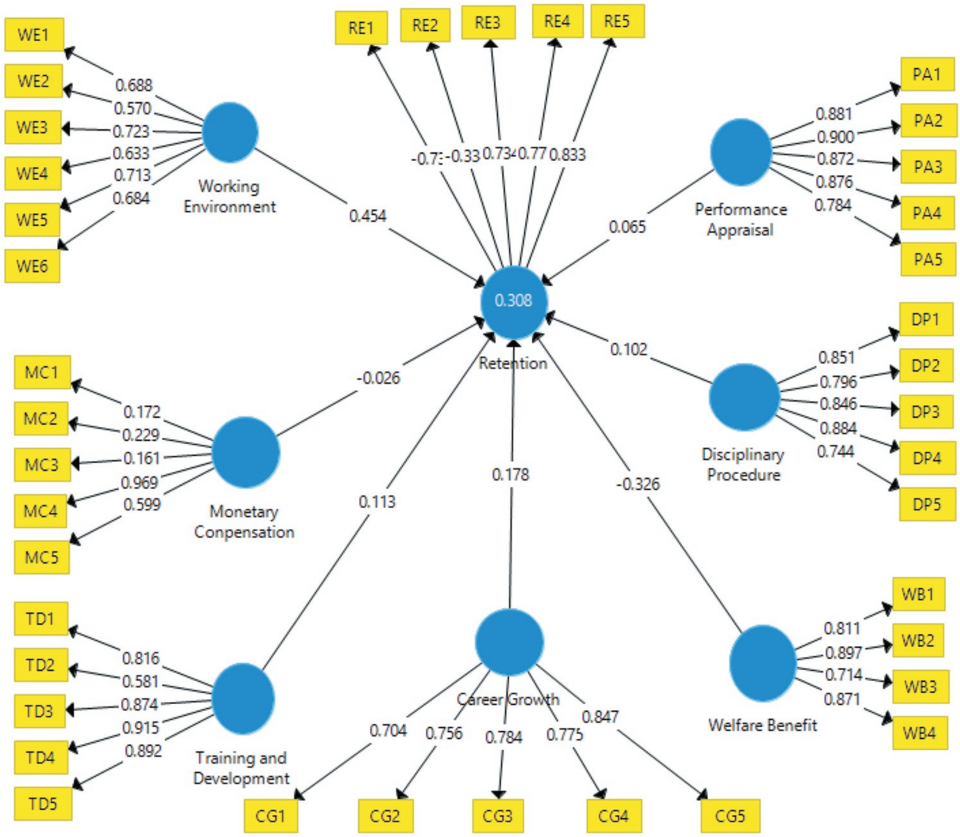

Figure A1 Measurement Model Based on PLS Algorithm for the Whole Constructs.

Table A1. Discriminant Validity (Cross-Loading Criterion).

Items	Career Growth	Disciplinary Procedure	Performance Appraisal	Retention	Training & Development	Welfare Benefit	Working Environment
CG1	**0.709**	0.447	0.517	0.199	0.546	0.510	0.266
CG2	**0.755**	0.588	0.409	0.168	0.221	0.347	0.246
CG3	**0.799**	0.476	0.698	0.352	0.402	0.392	0.244
CG4	**0.772**	0.647	0.591	0.312	0.488	0.524	0.386
CG5	**0.832**	0.656	0.525	0.324	0.376	0.392	0.342
DP1	0.621	**0.847**	0.563	0.327	0.339	0.305	0.285
DP2	0.650	**0.809**	0.616	0.372	0.435	0.469	0.448
DP3	0.562	**0.845**	0.561	0.333	0.369	0.389	0.437
DP4	0.606	**0.885**	0.584	0.337	0.355	0.330	0.384
DP5	0.559	**0.724**	0.426	0.140	0.331	0.378	0.322
PA1	0.605	0.588	**0.879**	0.397	0.560	0.476	0.401
PA2	0.606	0.624	**0.898**	0.327	0.443	0.438	0.369
PA3	0.636	0.585	**0.872**	0.327	0.445	0.499	0.487
PA4	0.674	0.639	**0.875**	0.349	0.476	0.510	0.369
PA5	0.649	0.485	**0.793**	0.231	0.393	0.378	0.303
RE3	0.319	0.316	0.352	**0.799**	0.368	0.175	0.385
RE4	0.196	0.261	0.198	**0.775**	0.083	−0.048	0.248
RE5	0.370	0.360	0.368	**0.855**	0.297	0.255	0.409
TD1	0.435	0.347	0.484	0.213	**0.810**	0.588	0.457
TD2	0.337	0.418	0.353	0.035	**0.551**	0.481	0.356
TD3	0.417	0.363	0.431	0.253	**0.871**	0.498	0.436
TD4	0.485	0.411	0.484	0.324	**0.918**	0.571	0.502
TD5	0.506	0.410	0.502	0.332	**0.901**	0.608	0.517
WB1	0.489	0.352	0.463	0.151	0.488	**0.837**	0.457
WB2	0.495	0.386	0.502	0.173	0.657	**0.890**	0.578
WB3	0.410	0.436	0.327	0.061	0.420	**0.679**	0.329
WB4	0.444	0.383	0.442	0.143	0.538	**0.873**	0.431
WE1	0.330	0.393	0.350	0.268	0.459	0.425	**0.690**
WE2	0.204	0.394	0.265	0.272	0.264	0.276	**0.557**
WE3	0.290	0.297	0.408	0.346	0.479	0.425	**0.748**
WE4	0.081	0.161	0.065	0.270	0.284	0.203	**0.609**
WE5	0.256	0.279	0.343	0.314	0.320	0.402	**0.720**
WE6	0.397	0.344	0.348	0.273	0.391	0.516	**0.684**

Note: Value in the diagonals cell (**bold**) represents the square root of AVE

Table A2 Collinearity Statistics on Outer Variance Inflation Factor (VIF) Values.

Measures	VIF
CG1	1.606
CG2	1.934
CG3	1.629
CG4	1.587
CG5	2.032
DP1	2.361
DP2	1.853
DP3	2.393
DP4	2.958
DP5	1.990
PA1	2.947
PA2	3.664
PA3	2.935
PA4	2.842
PA5	2.140
RE3	1.348
RE4	1.540
RE5	1.716
TD1	2.256
TD2	1.554
TD3	3.035
TD4	3.555
TD5	2.935
WB1	1.866
WB2	2.376
WB3	1.580
WB4	2.314
WE1	1.536
WE2	1.189
WE3	1.561
WE4	1.248
WE5	1.844
WE6	1.769