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Research Article

Determinants of COVID-19 Related Perception among University of Gondar Academic Staff, Gondar, Ethiopia, 2021: A Structural Equation Modeling Approach

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Introduction. Public perceptions of pandemic risk and prevention measures influence adherence to COVID-19 prevention efforts. Even though several factors influence public perceptions, there has been no research on the predictors of COVID-19-related perception in Ethiopia and there are few articles among academic staff worldwide. Thus, this study aims to assess predictors of COVID-19-related perception among Gondar University academic staff. *Method*. Institutional based cross-sectional study was conducted from April 10 to May 10, 2021. Daniel Soper's calculator was used to determine the sample size. A simple random sampling technique was employed. Data were collected through a self-administered questionnaire and analyzed using Stata V14. Structural equation modeling was performed to identify determinants of COVID-19 related perception. A p value less than 0.05 and a 95% confidence interval of β were used to declare the statistical significance of the variables. *Result*. A total of 602 academic staff participated. Mean age of participants was 32.38 (±5.83) years. Family size ($\beta = 0.12$), chronic illness ($\beta = -0.19$), knowledge ($\beta = 0.11$), and cues to action ($\beta = 0.43$) were significantly associated with perceived susceptibility. Similarly, educational status ($\beta = -0.11$), perceived susceptibility ($\beta = 0.61$), and cues to action ($\beta = 0.13$) were significantly associated with perceived severity. Likewise, knowledge ($\beta = 0.11$) and cues to action ($\beta = 0.62$) were significant predictors of self-efficacy. Correspondingly, knowledge ($\beta = 0.23$), chronic illness ($\beta = 0.09$), profession ($\beta = -0.09$), perceived susceptibility ($\beta = 0.19$), perceived severity ($\beta = 0.23$), and self-efficacy ($\beta = 0.29$) were significant predictors of perceived benefit. Similarly, age ($\beta = -0.18$), profession ($\beta = 0.10$), and perceived susceptibility ($\beta = -0.39$) were significantly associated with perceived barriers. *Conclusion*. Several sociodemographic and other factors affect COVID-19 related perceptions. Intervention should consider those factors to improve COVID-19 prevention practice.

1. Introduction

COVID-19 is highly contagious; a person can contract it from an infected individual or an unknown source [1–3]. Adhering to primary prevention strategies is practical and the best alternative in resource-limited countries like Ethiopia [4]. To prevent the further spread of COVID-19, government agencies have to launch successful public health initiatives and the public must participate and adhere to the government's control measures. Adherence to those prevention measures depends on public perceptions about pandemic risk and response [5, 6].

Multiple health models suggest that risk perception (perceived susceptibility and severity), perception of benefit, barrier, and self-efficacy are major components of any behavior change. The health belief model (HBM) is the most frequently used of those models. According to the HBM, people follow certain health-promoting behavior if they perceive that; first, they are susceptible to a severe health threat, second, methods to relieve the threat are important enough, third, possible barriers are easy, and, fourthly, individuals should believe in their confidence on undertaking the health behavior. To limit and terminate the spread of the virus, an individual should adhere to the control measures, which are largely affected by their perceptions of risk, benefit, barrier, and self-efficacy of adhering to prevention and control measures [7].

Perceived susceptibility is an individual's perception of vulnerability to a certain risk [8]. In different studies, it is concluded that people decided to follow preventive behavior when they had potential health threats during COVID-19 pandemic [9–12]. Similarly, perceived severity is the belief about how serious the consequences of the condition would be [13]. In the case of COVID-19 prevention practice, studies done in different parts of the world revealed that perceived severity was associated with COVID-19 prevention practice [14, 15]. Perception of benefit is an individual's belief in the prevention measure's ability of minimizing risks [16]. Several investigations on predictors of COVID-19 voluntary compliance behaviors demonstrate the importance of believing that taking health precautions will be effective in preventing COVID-19 [12, 17, 18]. Perceived barriers are the difficulties or costs to carry out the desired behavior and the most important predictor of prevention practice [12, 13, 18, 19]. Self-efficacy refers to the confidence or belief in one's abilities of engaging in protective behavior [20]. In the case of COVID-19, studies showed that self-efficacy was a significant predictor of preventive behavior from COVID-19 [18, 19].

In order to influence people's behavior to follow the COVID-19 health recommendations, it is important to understand how people perceive the COVID-19 pandemic risks, prevention barriers, benefits, and self-efficacy to change their behaviors [21]. Diverse demographic, sociopsychological, and structural variables may influence perceptions and, thus, indirectly influence health-related behavior. Knowledge and sociodemographic factors, particularly educational attainment, are believed to have an indirect effect on behavior by influencing the perception of susceptibility, severity, benefits, barriers, and self-efficacy [13]. For example, a study done in the Philippines showed that better knowledge of COVID-19 was positively associated with perceived vulnerability [22]. Similarly, study done in Belgium, on 1500 respondents about the intention to use contact identifying applications, revealed that age was significantly associated with perceived susceptibility, severity, benefit, and self–efficacy whereas it is not associated with perceived barriers. Additionally, gender, educational status, and health condition are not significantly associated with the perception of susceptibility, severity, benefits, barriers, and self-efficacy [23]. Those COVID-19 related perceptions are also highly correlated. For example, studies done in Iran and Sudan showed that perceived susceptibility, severity, and self-efficacy were positively correlated with perceived benefit [15, 24]. Similarly, a study done in Macao, China, shows that cues to action significantly correlated with perceived susceptibility, severity, and self-efficacy [25].

The University of Gondar like other higher education institutions in Ethiopia canceled face-to-face education for more than 8 months and restarts the usual face-to-face education in October 2020. Despite several factors contributing to those public perceptions and the urgent need for the evidence to raise COVID-19 prevention practice to the level of investigator's knowledge, there is no study done on predictors of COVID-19-related perception in Ethiopia and academic staff worldwide. Hence, this study provides important evidence inputs for designing programs to address COVID-19-related perception that is observed in the study population. It also contributes evidence inputs for preparing messages and materials for media campaigns to raise COVID-19-related perceptions. Additionally, the study will become a reference to the behavior of academicians in the prevention and control of similar pandemics that might emerge in the future. Considering those and similar rationale, this study aimed to assess predictors of COVID-19-related perception among Gondar University academic staff.

2. Method

2.1. Study Design, Period, and Setting. An Institutional based cross-sectional study was conducted from April 10 to May 10/2021 at the University of Gondar, located in the historical town Gondar. Currently, the University of Gondar has 5 Campuses, namely, CMHS (college of medicine and health sciences), Maraki, Aste Tewodros, Atse Fasil, and Teda campus. Gondar University gives 87 undergraduate, 137 master's, and 29 PhD programs for approximately 45,000 students. According to the university human resources department's first-quarter report of 2013 E.C, Gondar University had 8,019 staff, of whom 2,774 are academic staff.

2.2. Population and Sample. All academic staff of the University of Gondar were the source population for this study. To be among an academic staff of the University of Gondar and present at the university during the data collection period were the inclusion criteria. Academic staff of the University of Gondar who are under study in some other area and currently at the University of Gondar for vacation are excluded.

Regarding sample size, the study employed structural equation modeling analysis, so we have used Daniel Soper's free statistic sample size calculator for SEM [26]. The calculator computed the sample size required for a study that uses an SEM. We have used an anticipated effect size of 0.3 (medium) which is the usual effect size, the desired statistical power level of 0.8, seven latent and fifty-three observed variables in the model, and a type 1 error rate of 0.05 which gives a sample size of 560 participants [26]. Considering a 10% nonresponse rate, the final sample size was 616.

To select the study participants, the sample size was proportionally allocated to those five campuses (2,774 academic staff) based on the number of academic staff that they had. Finally, using the human resource department registration of each campus as a sampling frame, a simple random sampling method was employed for selecting study units from each campus using a computer-generated random number.

2.3. Study Variables and Measurement. In a multivariate analysis, variables are classified into four categories involving endogenous, exogenous, latent, and observed variables [27]. In this regard, COVID-19 prevention practices, perceived susceptibility, severity, benefit, barriers, and self-efficacy, were latent endogenous variables, and all items or indicators that are used to measure each construct of the health belief model were observed endogenous variables. A cue to action was an exogenous latent variable. Sociodemographic characteristics, such as age, sex, religion, marital status, educational status, monthly income, family size, and number of rooms per family, along with COVID-19-related knowledge, field of study (profession), chronic disease status, and likelihood of accepting COVID-19-related recommendation, were observed exogenous variables in this model.

2.3.1. COVID-19 Prevention Practice. Is the level of practicing COVID-19 prevention precautions met? And how individuals perform the measures in day-to-day life? It was measured by 8 questions containing five-point Likert scale (0 = never, 1 = rarely, 2 = sometimes, 3 = often, and 4 = always); the score lies in 0–32 [12] ($\alpha = 0.89$).

2.3.2. Perceived Susceptibility. It was measured by 6 questions containing five-point Likert scale; the score lies in 6–30. A higher score indicates high perceived susceptibility to COVID-19 [28] ($\alpha = 0.87$).

2.3.3. Perceived Severity. It was measured by 5 questions containing five-point Likert scale; the score lies in5–25. A higher score indicates high perceived severity of COVID-19 [12] ($\alpha = 0.83$).

2.3.4. Perceived Benefit. It was measured by 6 questions containing five-point Likert scale; the score lies in 6–30. A higher score indicates a high perceived benefit of COVID-19 prevention measures [19] ($\alpha = 0.90$).

2.3.5. Perceived Barrier. It was measured by 8 questions containing five-point Likert scale; the score lies in 8–40. A higher score indicates a high perceived barrier of COVID-19 prevention measures [19] ($\alpha = 0.90$).

2.3.6. Self-Efficacy. It was measured by 4 questions containing five-point Likert scale; the score lies in 4–20. A higher score indicates high self-efficacy in practicing COVID-19 prevention measures [12] ($\alpha = 0.86$).

2.3.7. Cues to Action. Strategies to activate one's readiness to use COVID-19 prevention practices were measured by 4 questions containing five-point Likert scale; the score lies in 4–20. A higher score indicates having high cues to action [12] ($\alpha = 0.83$).

2.3.8. COVID-19 Knowledge. It was measured by 8 items regarding prevention, transmission, sign, and symptoms of COVID-19. Each correct response was scored 1 and each incorrect response was scored 0. The score lies in 0–8 and a higher score indicates high COVID-19 knowledge [12].

2.4. Data Collection Tool and Procedures. First, an elicitation study was conducted on 18 academic staff from the study population using guidelines prepared based on the construct of HBM. The salient beliefs that are raised by the elicitation are incorporated into the tool preparation. Then, data was collected through a self-administered interview with a pretested structured questionnaire, which was adapted by reviewing different literature and WHO prevention recommendations by contextualizing it in the form of the VL Champion instrument scale of health belief model constructs [12, 19, 28–30]. The interview questionnaire consists of four parts. The determinant factors including sociodemographic variables are the first part of the tool and contain eleven items. Part II contains items used to assess COVID-19 prevention practices (8 items). Part III contains six subparts, which assess those COVID-19-related perceptions (perceived susceptibility (6 items), perceived severity (5 items), perceived benefit (6 items), perceived barriers (8 items), self-efficacy (4 items), and cues to action (4 items)). Part IV contains items used to assess COVID-19-related knowledge (8 items) (Supplementary Table 1).

The data were collected by five first-year MPH students. They were trained for two days by the principal investigator. Two assistant lecturers supervised the procedure of the data collection.

2.5. Data Quality Assurance. To keep data quality, the questionnaire (English version) is translated into Amharic and back-translated to English by two different persons. Two days of training was given to the data collectors on the objective, relevance of the study, confidentiality of information, respondent's right, informed consent, and prevention precaution that they should follow during data collection. To check content validity, the questionnaire was given to three health behavior experts who have assistant professors and above qualifications; two medical doctors and one infectious disease professional (6 in total) checked its relevance and gave their comments. Finally, the investigator incorporated the comments and prepared the final draft of the tool for data collection. The questionnaire was pretested on Gondar teachers training college academic staff on 5% of the final sample. After pretesting, amendments were made. The supervisors made frequent checks on the data collection process to ensure the completeness and consistency of the gathered information.

2.6. Statistical Analysis and Model Assumptions. After collection, data were entered using EpiData version 4.6 statistical software and then exported to SPSS version 25 for further data management. Variable coding and transformations were done to make the dataset ready for analysis. Then, descriptive analysis such as proportions, percentages, measures of central tendency and dispersion, tables, and graphs was done. Structural equation modeling analysis was performed to identify determinants of COVID-19-related perception using Stata version 14. First, we built a measurement model to test whether the observed variables reliably reflect the latent variables (i.e., prevention practice, perceived susceptibility, severity, benefits, barriers, self-efficacy, and cues to action). This measurement part implies confirmatory factor analysis (CFA) that is determining the construct validity of the tool. Thereafter, once the measurement parts of all health belief model constructs are determined; then, we framed the structural model considering COVID19-related perception (perceived susceptibility, severity, benefits, barriers, and self-efficacy) as an outcome variable and COVID-19 prevention practice as the final outcome variable. The model fitness was evaluated through several fit indices, including the chi-square to the degree of freedom ratio of 5 or less, root mean square error of approximation (RMSEA) values below 0.06, and the standardized root mean square residual (SRMR) values less than 0.08 indicating good model fit [31–33]. A p value of less than 0.05 and a 95% confidence interval were used to declare statistical significance.

As a model assumption, the multivariate normality test was done and the data that deviated from the multivariate normality assumption as Mardia's skewness and kurtosis test of normality are significant [34]. Hence, robust correction of the Satorra-Bentler estimation technique was used [35]. The large sample size was another assumption of SEM in which we have used a standard sample size calculator for SEM which gives the sample required to detect and estimate the hypothesized model structure [26]. Another assumption of SEM is correct model specification; in our case, we have used the HBM which is a verified behavioral model which supports the specified model going with theory [21]. Our model is properly specified with an overidentified (positive degree of freedom (1018 in our case)) model structure. No multicollinearity is also the assumption of SEM in which in our case it is checked by making a correlation matrix of items. The result supports that multicollinearity is not an issue in our data since the correlation of all items in the correlation matrix is less than 0.8 [36]. Furthermore, multiple measurements (three or more items must be used to measure a construct) are assumptions of SEM. In our case, the minimum number of measurement items per construct was four (for cues to action and self-efficacy) [27].

2.7. Ethical Consideration. Ethical approval was obtained from the IRB (institutional review board) of the University of Gondar with letter reference no. IPH/1414/2013. An official letter of permission was written to each college of the University of Gondar from the Institute of Public Health. Following an explanation of the purpose of the study, written informed consent was obtained from participants. Also, affirmation was made that they are free to withdraw the consent and discontinue participation without any form of prejudice. Confidentiality of information and privacy of participants were assured for all the information provided, to preserve the confidentiality of the data in order not to be exposed to the third party except investigators. Furthermore, to avoid possible harm (infection transmission to participants), the data collectors strictly follow prevention precautions such as wearing a facemask and using sanitizer.

3. Results

3.1. Sociodemographic Characteristics of the Respondents. A total of 602 academic staff participated with a 97.7% response rate. The mean age with standard deviation (SD) of the respondents was 32.38 (±5.83) years. More than three-fourth of the respondents were males (80.2%) and orthodox religion followers (82.4%). Regarding marital status, more than half (58%) of them were married and 77.1% of them were master holders. More than two-thirds (69.3%) of the respondents had a family size of 1–3. Nearly, two-thirds (64.8%) of the study respondents had 1-2 rooms per family. The mean monthly income of the participants was 10,789 (±2,786.37) E. birr (Table 1).

3.2. Other Determinants of COVID-19 Perception. Regarding chronic illness status, 570 (94.7%) of the respondents had no known chronic illness. More than one-third 233 (38.7%) of the respondents were from the health-related field. Regarding the likelihood of accepting COVID-19-related recommendations, only 211 (35%) of the respondents were very so much likely to accept it.

Concerning COVID-19-related knowledge, the median knowledge score of the respondents was 8 with an IQR (interquartile range) of 7 to 8. [7, 8].

The mean perceived susceptibility score of the study participants was 18.35 (±5.83). Regarding the perceived severity of COVID-19, the mean perceived severity score was 16.8 (±4.72). Similarly, the mean score with SD of perceived benefit, barriers, self-efficacy, and cues to action was 24.17 (±5.03), 24.44 (±7.75), 13.67 (±3.86), and 14.2 (±3.64), respectively. Regarding COVID-19 prevention practice, the mean score of practice is 18.34 and SD is 6.79 (Table 2).

3.3. Determinants of COVID-19-Related Perception Based on SEM Analysis. Structural equation model analysis was done in two steps. In the first step, the assessment of the measurement model was done with seven-factor CFA. Secondly, the model containing the seven-factor and modifying variables was run to verify relationships and associations among exogenous and endogenous variables.

3.4. Measurement Part of SEM. From the start, Kaiser-Meyer-Olkin (KMO) sample adequacy test was conducted and it was 0.924 which supports the fact that the sample was

Table 1: Sociodemographic characteristics of academic staff of University of Gondar, Ethiopia, 2021 ($n = 602$).

Variable		Frequency	Percent
Age	20–28	159	26.4
	≥29	443	73.6
Sex	Male	483	80.2
	Female	119	19.8
Religion	Orthodox	496	82.4
	Muslim	54	9.0
	Protestant	48	8.0
	*Other	4	0.7
Marital status	Single	245	40.7
	Married	349	58.0
	Divorced	7	1.2
	Widowed	1	0.2
Educational status	Degree	108	17.9
	Master	464	77.1
	PhD and above	30	5.0
Family size	1–3	417	69.3
	4–6	169	28.1
	≥7	16	2.7
No. of rooms per family	1-2	390	64.8
	≥3	212	35.2
Income	≤9056	198	32.9
	9057–14999	354	58.8
	≥15000	50	8.3

*Others are catholic and do not have a religion.

adequate to proceed with factor analysis. Similarly, Bartlett's test of sphericity was significant with $p = 0.000$, indicating that the correlation matrix among items was not an identity matrix [37]. Then, the measurement model was done with seven-factor CFA. On the CFA, all the standardized factor loading of prevention practice, perceived susceptibility, severity, benefit, barrier, self-efficacy, and cues to action was >0.5 with a p value of less than 0.05 (Supplementary Table 1).

3.5. Determinants of COVID-19-Related Perception: Structural Part of SEM. Sociodemographic and other factors (age, sex, family size, number of rooms, educational status, income, the field of study (profession), chronic disease status, and knowledge) were included as predictors for COVID-19-related perception (perceived susceptibility, severity, benefit, barrier, and self-efficacy).

Family size ($\beta = 0.12$, $p < 0.05$), chronic illness (not having) ($\beta = -0.19$, $p < 0.05$), knowledge ($\beta = 0.11$, $p < 0.05$), and cues to action ($\beta = 0.43$, $p < 0.05$) were significantly associated with perceived susceptibility to COVID-19. Similarly, educational status ($\beta = -0.11$, $p < 0.05$), perceived susceptibility ($\beta = 0.61$, $p < 0.05$), and cues to action ($\beta = 0.13$, $p < 0.05$) were significantly associated with perceived severity to COVID-19.

At the same time, knowledge ($\beta = 0.11$, $p < 0.05$) and cues to action ($\beta = 0.62$, $p < 0.05$) were significant predictors of self-efficacy of COVID-19 prevention practice. Correspondingly, knowledge ($\beta = 0.23$, $p < 0.05$), chronic illness (not having) ($\beta = 0.09$, $p < 0.05$), profession (nonhealth) ($\beta = -0.09$, $p < 0.05$), perceived susceptibility ($\beta = 0.19$, $p < 0.05$), perceived severity ($\beta = 0.23$, $p < 0.05$), and self-efficacy ($\beta = 0.29$, $p < 0.05$) were significant covariates of perceived benefit of COVID-19 prevention measures. Likewise, age ($\beta = -0.18$, $p < 0.05$), profession (nonhealth) ($\beta = 0.10$, $p < 0.05$), and perceived susceptibility ($\beta = -0.39$, $p < 0.05$) were significantly associated with perceived barriers of COVID-19 prevention practice (Table 3).

Table 2: Magnitude of COVID-19-related perception of the academic staff of the University of Gondar, Ethiopia, 2021 ($n = 602$).

Variable	Minimum	Maximum	Score mean (±SD)
Perceived susceptibility	6	30	18.35 (±5.83)
Perceived severity	5	25	16.8 (±4.72)
Perceived benefit	6	30	24.17 (±5.03)
Perceived barrier	8	40	24.44 (±7.75)
Self-efficacy	4	20	13.67 (±3.86)
Cues to action	4	20	14.2 (±3.64)
COVID-19 prevention practice	0	32	18.34 (6.79)

3.6. Indirect Effects of Sociodemographic and Other Factors on COVID-19 Prevention Practice. As we have explained above, sociodemographic and other factors are predictors of COVID-19-related perception so they indirectly affect COVID-19 prevention practice through those perceptions. Regarding this indirect effect, a unit increase in SD of age, family size, and knowledge resulted in 0.07, 0.05, and 0.12 SD increments in practice, respectively. However, an increase in educational status results in a 0.01 SD decrement in practice. Similarly, prevention practice declined by 0.06 SD among participants not having a chronic illness as compared to those having a chronic illness. Likewise, prevention practice is decreased by 0.05 SD among nonhealth-related academic staff as compared to health-related academic staff (Table 4).

The final structural equation modeling analysis showed good model fit indices (Satorra-Bentler chi-square to the degree of freedom ratio of 2724/1018 = 2.68, Satorra-Bentler RMSEA 0.053, and SRMR 0.074) [31–33]. The model explained a huge variance in COVID-19 prevention practice as 55% of the variance of practice was explained by the model. Moreover, 25%, 46%, 40%, 20%, and 40% of the variance in endogenous latent variables: perceived susceptibility, perceived severity, perceived benefit, perceived barrier, and self-efficacy were explained by the model covariates, respectively (Figure 1).

4. Discussion

This study found the predictors of COVID-19-related perception and the indirect effect of those predictors on COVID-19 prevention practice. In this regard, this study found that perceived susceptibility decreased among participants not having chronic illness compared to those having a chronic illness, which indirectly resulted in decreased practice among those not having a chronic illness. This finding is complemented by studies done in Italy and

Table 3: Standardized regression weights of predictors of COVID-19-related perception among academic staff of the University of Gondar Ethiopia, April 2021 ($n = 602$).

Variable	B	95% conf. interval of β LB	95% conf. interval of β UB	p value	Variance explained (%)
Susceptibility					
Family size	0.12	0.05	0.18	0.000	25
Chronic illness	−0.19	−0.26	−0.11	0.000	
Knowledge	0.11	0.03	0.18	0.006	
Cues to action	0.43	0.35	0.51	0.000	
Severity					
Educational status	−0.11	−0.17	−0.04	0.001	46
Susceptibility	0.61	0.53	0.69	0.000	
Cues to action	0.13	0.04	0.22	0.004	
Self-efficacy					
Knowledge	0.11	0.04	0.18	0.002	40
Cues to action	0.62	0.56	0.68	0.000	
Benefit					
Knowledge	0.23	0.17	0.29	0.000	40
Chronic illness	0.09	0.03	0.16	0.005	
Profession	−0.09	−0.15	−0.03	0.002	
Susceptibility	0.19	0.09	0.30	0.000	
Severity	0.23	0.12	0.35	0.000	
Self-efficacy	0.29	0.21	0.38	0.000	
Barrier					
Age	−0.18	−0.25	−0.11	0.000	20
Profession	0.10	0.03	0.17	0.004	
Susceptibility	−0.39	−0.46	−0.31	0.000	

LB means lower bound; UB means upper bound.

Table 4: Standardized indirect and the total effect of socio-demographic and other factors on prevention practice of academic staff of the University of Gondar, Ethiopia, 2021.

Variable	Indirect effect β	p value
Practice		
PBA ← age	0.07	0.000
PSU ← family size	0.05	0.001
PSE ← educational status	−0.01	0.033
PBE, PSE, PSU ← knowledge	0.12	0.000
PSU, PBE ← chronic illness	−0.06	0.001
PBA, PBE ← profession	−0.05	0.001

PSE is perceived severity, PBE is perceived benefit, PBA is perceived barrier, SE is self-efficacy, and PSU is perceived susceptibility.

China in which Individuals with chronic diseases showed a greater perception of the risk of contagion [38, 39]. This implies the need to give more focus on increasing the perception of susceptibility among individuals not having chronic illness to raise their practice. Additionally, a raise in knowledge resulted in increased perceived susceptibility which later improved practice which is in line with a study done in the Philippines in which knowledge was significantly associated with perceived susceptibility [22]. The finding suggests that strong effort should be made to increase the knowledge of the participants to raise their perception so as to improve their prevention practice.

Regarding predictors of perceived severity, higher educational status resulted in decreased perceived severity which infers academic staff who are at higher education level perceive COVID-19 as less severe as compared to those at lower education level, which later lowered their practice. This finding is consistent with the study done in China in which participants with lower education backgrounds had significantly more protective behaviors than participants with higher education [40]. This might be due to when an individual knows more about the pathogenesis of the COVID-19 disease, they may perceive it as less severe by simple observation of sign and syptoms of the disease. Furthermore, a rise in perceived susceptibility and cues to action resulted in increased perceived severity of COVID-19. The latter finding is similar to a study done in China [25]. This finding implies intervention that aimed to increase susceptibility and cues to action which would increase an individual's perceived severity of COVID-19 and in turn improve his/her practice.

A raise in knowledge and cues to action increased self-efficacy which suggests that increasing COVID-19-related knowledge and exposure to cues to action increased their practice through increasing their self-efficacy. This implies that increasing COVID-19 awareness among individuals and providing possible triggers for prevention practice would improve people's self-confidence in practicing the prevention measures and help them to improve their actual practice.

A raise in knowledge leads to an increase in perceived benefit. In our study, perceived benefit decreased among nonhealth-related academic staff as compared to health-related staff which later resulted in decreased COVID-19 prevention practice among those nonhealth-related academic staff. This might be due to individuals who are out of

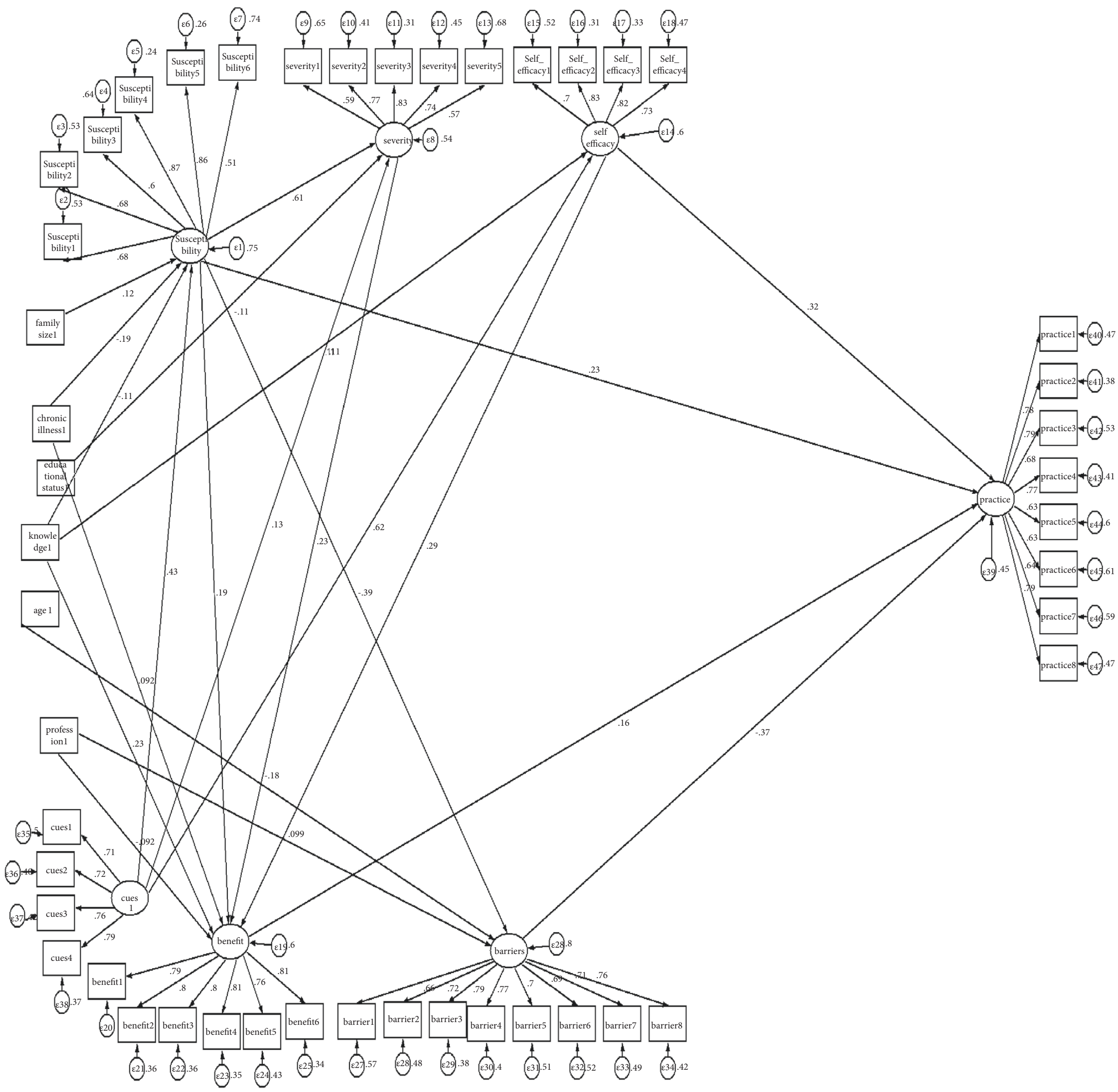

Figure 1: Structural equations modeling with standardized coefficients of COVID-19 prevention practice among academic staff of University of Gondar, Ethiopia, 2021, using the health belief model. *Note*. Statistically insignificant paths between variables are not presented.

the health field are less familiar with the infection prevention protocols which result in a decreased perception of the importance of those prevention protocols. This finding suggests that interventions to raise the perception of benefit should be more focused on those nonhealth-related academic staff to increase their practice. On the relationship of COVID-19-related perception, a raise in perceived susceptibility, severity, and self-efficacy resulted in an increment in perceived benefit of COVID-19 prevention measures and finally an increase in the practice of those measures. This finding is in line with studies done in Iran [24] and Sudan [15] in which perceived susceptibility, severity, and self-efficacy were positively correlated with perceived benefit.

In this study, perceived barrier increased among nonhealth-related academic staff as compared to health-related staff which implies that those difficulties are more noticeable in nonhealth-related academic staff as compared to health-related staff which in the end resulted in a decrease in practice on those nonhealth-related academic staff. The possible justification might be due to individuals who are out of the health field being new to the COVID-19 prevention measures so they may forget to apply them on a day-to-day base. The finding implies that intervention should more focus on those nonhealth-related academic staff to lower their perception of barriers so as to increase practice. Furthermore, increase in participant age resulted in a decreased perceived barrier which later resulted in increased practice. This finding is consistent with the study done in China in which participants of a lower age group practice fewer protective behaviors as compared to aged participants [40]. The finding suggests that intervention should more target lower age groups to decrease barriers and increase their practice. Similarly, a raised perceived susceptibility resulted in a decreased perceived barrier. This finding was complementary with studies done in Iran [24] and Sudan [15] in which perceived susceptibility negatively correlated with the perceived barrier. This might be due to when individual perceive that he/sheis susceptible to the disease he/she would try to overcome possible obstacles to reduce their vulnerability to the virus. This implies that strategies focused on increasing the perception of susceptibility lower the perception of barriers so as to improve prevention practice.

Notwithstanding its contribution of evidence, this study has some limitations. First, the study is limited to academic staff and did not consider other administration staff which makes it difficult to infer the finding to all staff of the university. Secondly, there was limited research done by HBM with structural equation modeling in the form of MIMIC models. This makes our discussion short and lacks detailed comparison. Furthermore, variables that have more than two categories such as religion, marital status, and the likelihood of accepting COVID-19-related recommendations are not included as they need to form dummy variables, but to minimize model complexity they are not included. A qualitative in-depth investigation may be needed to explore certain determinants of perception.

4.1. Strength of the Study. The present study had several strengths. First, it stands on a current and global issue. Secondly, it incorporates SEM as an analysis model for HBM which is capable of rectifying failures of the basic model such as regression by considering the error of measurement and showing indirect and other complex relations. Behavioral concepts such as practice, perception, motivation, attitude, and self-efficacy are difficult to measure and have complex relationships with other variables which increase the need to employ SEM analysis in behavioral research [32]. Furthermore, this study includes sociodemographic and other factors as exogenous predictors for COVID-19-related perception in the form of multiple indicators multiple cause (MIMIC) model which enable an explanation of unknown concept using two dimensions, that is, the cause and effect dimension [41].

5. Conclusion

COVID-19-related perceptions such as perceived barriers, self-efficacy, susceptibility, and benefit were the direct predictors for COVID-19 response behavior as proposed by the theoretical underpinning of the health belief model. Several sociodemographic and other factors affect COVID-19 related perceptions. Not having a chronic illness and a low level of COVID-19-related knowledge contribute to a low level of COVID-19 perceived susceptibility. A low level of COVID-19-related knowledge and low-level exposure to cues to action were the contributing factors to decreased perceived self-efficacy of COVID-19 prevention behavior. Likewise, perceived benefit decreased among nonhealth-related academic staff, individuals having lower perceived susceptibility, severity, self-efficacy, and COVID-19-related knowledge which later result in a decrease in their COVID-19 prevention practice. Conversely, perceived barriers increased among nonhealth-related academic staff, lower age groups, and individuals having lower perceived susceptibility which in the end resulted in a decrease in their COVID-19 prevention practice. Those findings indicate that intervention should more focus on nonhealth-related academic staff, individuals having a low level of COVID-19-related knowledge, lower age group, not having a chronic illness, and low-level exposure to cues to develop satisfactory COVID-19-related perception so as to improve COVID-19 prevention practice.

Abbreviations

CFA: Confirmatory factor analysis
HBM: Health belief model
IQR: Interquartile range
KMO: Kaiser–Meyer-Olkin
RMSEA: Root mean square error of approximation
SARS: Severe acute respiratory syndrome
SD: Standard deviation
SEM: Structural equation modeling
SRMR: Standardized root mean square residual
WHO: World health organization.

Data Availability

The result of this research was extracted from the data gathered and analyzed based on the stated methods and materials. All the relevant data are within the paper.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

AZ contributed to conceptualization of the study, methodology, validation, and statistical analysis coordinate data collection. AN, MW, EMM, AB, AH, and AK performed supervision, validation, writing, review, and editing. All authors read and approved the manuscript.

Supplementary Materials

The supplementary file shows items used to measure COVID-19-related perception and prevention practice, their score, and standardized factor loading (SFL) as cited in the respective place in the document. Supplementary Table1: item score and standardized factor loading (SFL) of COVID-19-related perception and prevention practice measure. (*Supplementary Materials*)

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