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An assessment of m-health effect on COVID-19 management using PLS modeling approach

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ABSTRACT

Introduction: The aim of the present study was to investigate the different roles of m-Health in pandemic management using the Partial Least Square (PLS) modeling technique. Owing to the limited existing literature regarding theorizing and the lack of the default model in predicting the role of m-Health in pandemic management, this method was used for exploratory modeling.

Material and Methods: The PLS model was performed with smart-PLS software for the following steps: estimating weight ratios, considering weight ratios as input, estimating parameters, model-fitting and testing hypotheses. In addition, Factor scores in regression equations were used to estimate structural parameters. PLS algorithm, Cronbach's alpha, and Composite Reliability were used for the measurement and reliability evaluation model Goodness-of-fit. In addition, the R2 index was used to evaluate the model adequacy. Bootstrapping was used for significant coefficients. The Goodness-of-fit of the model was examined via the Standardized Root Mean Square Residual (SRMR) criterion.

Results: It is determined the measurement models goodness-of-fit which the alpha values were as follows: diagnosis construct=0.786, follow-up=0.772, treatment=0.796, health care providers=0.704 and education=0.839 with more than 0.7 for all measures for Composite Reliability, the structural model measures such as R2 were higher than 0.6 for all areas and the overall model goodness-of-fit was -0.007 for SRMR, the five hypotheses developed in the model were confirmed according standardized coefficients more than 1.96 for all paths. Furthermore, the proposed model concerning the positive and significant role of m-Health in diagnosis, treatment and follow-up, education and health providers during the pandemic era was approved.

Conclusion: The results of the present study can be used as a theoretical basis in developing models related to the role of m-Health in pandemic management. Also, health policymakers and practitioners could use the results to manage current and post-coronary conditions and to promote services based on various m-Health apps.

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INTRODUCTION

The growth of information technology in recent decades has brought significant advances in the health system and has improved access to information by upgrading hardware and software [1].

Mobile health (m-Health), as one of the most important and widely used sub-categories of electronic Health (e-Health), describes any type of health care activity supported by mobile devices. For example, a m-Health application (app) can help health professionals treat illnesses, educate patients about self-care, and adhere to treatment [2]. The use of m-Health apps reduces unnecessary hospital visits and, as a result, reduces the mobility of patients with weakened immune systems to high-risk areas [3]. Mobile-based distance counseling can be used for high-risk groups such as the elderly, pregnant women who are unable to visit in person [4].

In the Ebola and Zika epidemics, m-Health apps led to improved access to testing, communication tracking, support for health workers, and increased community knowledge. Recent studies have pointed to the potential of m-health to provide mental health services in support of patients and health care providers in dealing with the psychological effects of the COVID-19 pandemic [5]. M-Health provides telemedicine services for counseling patients with coronary heart disease and psychologically in need of counseling. By using these facilities, in addition to increasing the patient's sense of satisfaction with counseling services, the effectiveness of care services during the pandemic increases [6]. Many countries used mobile data to respond quickly to COVID-19. This process includes collecting anonymous data to track the movement of people and track cell phones to track down suspicious cases and their communications [7]. Call tracking apps have been an important program of countries such as China, South Korea, Singapore, and the United Kingdom responding to the COVID-19 pandemic [5]. Smartphones are able to collect big data through sensors such as the Global Positioning System (GPS) to collect data on population movement patterns, not just to implement social distance and isolation but also able to model the epidemiological spread of the virus. Smartphones are also able to facilitate timely interventions to improve people's behavior and communication with health providers, support risk assessment, case identification, tracking and monitoring [8, 9]. Integration of epidemiological and geographical data on the prevalence of communicable diseases in an area can help track cases that are themselves an effective tool in controlling the spread of infection [3].

Iran, as one of the countries that has had a great impact since the beginning of the COVID-19 pandemic, in addition to extensive treatment measures, has also carried out activities to monitor the disease through mobile technology, including the development of Mask and AC19 mobile apps for self-assessment and patient communication tracking. From the first days of the pandemic, the government and the Ministry of Health in Iran sent text messages to all people in the form of educational and preventive measures, and by creating a web-based self-assessment app and introducing it, people were monitored and screened [10]. In addition to the government, health care providers can also use the potential of m-Health to improve the quality of their services such as education, counseling and follow-up of patients [4]. The following sections of the research according to the objectives that are mentioned below include the following: In the second section, related studies are reviewed and the purpose of the research is explained. In the third part methods and in the fourth part, the results are presented and then the discussion and conclusion are described.

The studies that have been done so far in the field of m-Health and pandemic fall into four general categories. The first category is studies that have systematically reviewed the m-Health apps in this period. Adans-Dester et al. divide the application of m-Health technology in the field of pandemic management into three general categories: e-PRO systems, which include digital systems for collecting reports from patient outcome, and for collecting signs and symptoms from patients in line with Infection predictions. Wearable sensors were used to monitor physiological symptoms such as fever, increased respiration and heart rate, and decreased oxygen saturation, and digital contact tracking technologies were used to identify people who were positively related. The integration of these technologies and the creation of an integrated solution provide an opportunity to develop tools for screening, risk measurement, early detection, referral of suspects for testing, isolated and quarantine monitoring, ensuring compliance with social distance laws, providing remote care and recovery monitoring [11]. Asadzadeh et.al in a systematic review has classified the applications of m-Health in pandemic management into four categories of prevention, diagnosis, treatment and protection. Mobile apps and text messages were among the most widely used tools. The next categories included wearable sensors, portable screening tools, tele-health, and remote monitoring [12].

Another group of studies have reviewed and evaluated COVID-19 m-Health apps contents and functions. Ming et al. reviewed the content of corona m-Health apps in their study and concluded that most IOS apps provide a geographic map of the distribution of corona patients, while android-based apps have options to monitor patients at home. They conclude that in order to guide the audience in choosing the right app during the pandemic, it is very important that these tools be evaluated and categorized through scientific methods [3]. Chidambram et al. in a study evaluating COVID-19 applications in the UK, and categorize them in three areas of diagnosis, call tracking and information provision. M-Health apps introduced by the government were the most used among users. Also, the effectiveness of call tracking applications is challenged by issues such as the confidentiality of user information [13]. Bassi et al. in a study concluded that m-Health apps in India generally operated in the areas of self-care, quarantine monitoring and call tracking. Given the role of applications in disseminating information about the disease, these tools will greatly assist the Indian government in responding quickly to pandemics [5].

The third category of studies generally address the use of m-Health in pandemic management, their opportunities and challenges. Ekong et al concluded that the ability to track calls through mobile health applications plays a very important role in the management of pandemic, but one of the most important challenges the confidentiality of patients' information, which can be addressed through strategies such as obtaining patient consent, anonymizing patient identities, and tracking contacts only in public places [7]. Zamberg et al. believed that health issues accompanied in transmission COVID-19 health data is very useful among institutions and leads to an increase in data transfer speed and at the same time leads to an increase in staff self-awareness in performing daily work activities [14]. The fourth category of studies is discussed COVID-19 application development [14, 15]. To the best of our knowledge, no study ever has modeled the role of m- Health in pandemic management. The modeling process helps health professionals to identify errors more quickly with a deep understanding of the target population and existing variables, have a basis for analyzing existing data, and at the same time, predict future situations [16]. Also, have in the present study, with the aim of modeling the application of mobile health in the management of the COVID-19 pandemic, the initial theoretical basis for the role of this technology will be provided not only in the COVID-19 pandemic but also for similar situations in the future. The results of the present study will increase the awareness of health policy makers and managers; provide them with a higher decision-making ability, and more optimal use of existing tools and infrastructures in line with better performance management. In addition, mobile health developers will gain a deeper understanding of the different areas that can serve using the results of this study. Furthermore, health researchers will have an initial theoretical basis for hypothesizing, model generation, and identification of influencing variables in the electronic health field.

Therefore, the aim of this study was to investigate the different roles of m-Health in pandemic management using Partial Least Square (PLS) modeling technique. However, the limited existing research literature concerning theorizing and pre-modeling the role of m-Health in pandemic management made us implement exploratory modeling. Hence, the research was developed through two main steps, which included reviewing literature and formulating hypotheses, developing the initial model and ultimately testing the proposed model.

Hypothesis Development

Based on the background of the research, 5 primary hypotheses were designed regarding the role of mobile health in the management of the COVID-19 pandemic, which were evaluated using the structural equation method.

Hypothesis 1: M-Health has a positive and significant effect on the diagnosis of COVID-19

Hypothesis 2: M-Health has a positive and significant role in educating people about corona-related topics

Hypothesis 3: M-Health has a positive and significant role in the COVID-19 follow-up.

Hypothesis 4: M-Health positively and significantly afford health providers to manage pandemic.

Hypothesis 5: M-Health has a positive and significant role in the COVID-19 treatment.

According to the initial research hypotheses and the existing literature, the initial research model was developed with the following procedures (Fig 1).

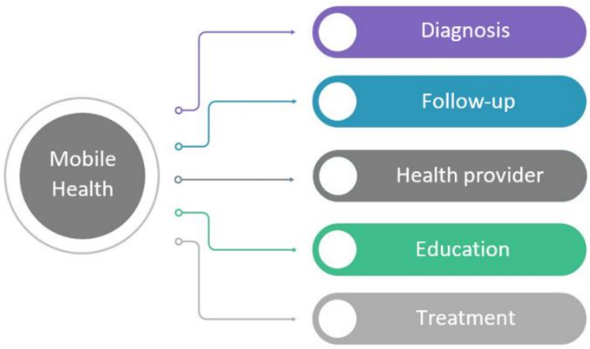

Fig 1: Initial research model

MATERIAL AND METHODS

The present study is a cross-sectional study. The study population includes all clinical and preclinical personnel providing health services in training hospitals of Iran. Because of different groups such as doctors, nurses, radiologists, laboratory personnel and health information technology specialists, we applied stratified random sampling to divide the estimated sample according to the number of populations in each group. The researcher-made questionnaires were administered among 250 people, and finally 200 completed questionnaires were collected and reviewed.

A researcher-made questionnaire was used to assess the staff's perspective. For the initial design, the questions were designed through initial questions review, then the initial structure was developed by modeling another researcher-made questionnaire in a similar study. The questionnaire included three general parts: The first part encompassed the demographic information which measured variables such as age, gender, degree and level of education, work experience. In the second part, multiple-choice questions were designed in which respondents were asked questions (5 questions) about the source that receives information about the COVID-19, the use of mobile phones to provide medical services and communication with patients during the pandemics.

The third section consisted of questions 6 to 30 in five parts: diagnosis, treatment, follow-up, education, and health care providers.

Due to the prevalence of COVID-19 disease and in order to comply with health protocols, the questionnaire was designed electronically using the google doc platform and the link to the questionnaire was emailed and the related links were shared with virtual groups of personnel Information on messengers and other resource-sharing platforms (COVID-19 virtual staff training pages available on the university website or other related websites). To encourage the staff in completing the questionnaire, the information and educational aspects of the questionnaire were emphasized. Respondents were also asked to share the questionnaire if they were involved in a specialized group in cyberspace.

Each time the questionnaire is completed, the answers are stored electronically in the google sheet database, and ultimately, when the sample limit is reached, the database will be analyzed via an Excel file.

Independent variables and predictors considered (potential confounders) in the study are as follows: gender (male / female), age (less than 30 years / 30-30 years / 50-41 years / over 50 years), Education level (diploma / associate degree / bachelor`s / master`s / professional doctorate / specialist / subspecialty), field of study, city of work, service history (less than 5 years / 10-5 years / 15-10 years / over 15 years) , tools utilized to increase health information in the pandemic period (social networks (Instagram, Facebook, Twitter) / Messengers (Telegram, WhatsApp) / Public health databases (PubMed, Scopus) / Health apps) , using mobile to communicate with the patients in the pandemic period (yes / no), tools used to communicate (SMS) / Social networks (Instagram, Facebook, Twitter) / Messengers (Telegram, WhatsApp), the purpose behind mobile utilization to communicate with patients in the pandemic period (education / information / treatment / follow-up / diagnosis), questions related to measuring the attitude of employees towards service through mobile phones and their subscales –i-e- diagnosis, treatment, follow-up, training, providers were the areas of interest.

The least squares (PLS) modeling, a variance-based technique with a high flexibility in contrast to covariance-based structural models, was considered for modeling purpose. It should be noted that PLS does not require a large sample size and hence is not sensitive to the assumption of normality [17]. The steps performed for the PLS model with smart PLS software are: estimation of weight ratios, weight ratios as input, estimation of parameters, model goodness–of-fit and hypotheses testing. Factor scores in regression equations were also used to estimate structural parameters.

PLS algorithm and Cronbach's alpha and Composite Reliability (values above 0.7 suitable) were used to evaluate the reliability and how well the measurement model fits. The R^2 index was used to evaluate the adequacy of the model (0.67= significant, 0.33=moderate, and 0.19=weak) [18]. Bootstrapping was also used to test the significance of coefficients. The model goodness-of-fit was evaluated via SRMR (less than 0.08 or 0.1) [19]. Also, demographic variables such as age, gender, level of education were included in the model and their effects was controlled, accordingly.

RESULTS

The total number of people surveyed were 200 staff of medical science hospitals. In addition, 106 (53%) of the participants were under 30 years old, 57 (28.5%) were between 30 and 40 years old, 34 (17%) were between 41 and 50 years old and 3 (1.5%) were over 50 years old. Also, 113 (56.5%) were female and 87 (43.5%) were male. Additionally, 196 (98%) of the participants utilized mobile phones to improve their health information during the pandemic period, of whom 68 (34%) applied social networks (Instagram, Facebook and Twitter), 61 (30.5%) referred to messengers (Telegram and WhatsApp), 40 (20%) used health apps, and 31 (15.5%) applied health science databases (PubMed and Scopus) to increase their information. Table1 presents demographic information of the participants.

The proposed model testing

To test the proposed research model, the model analysis algorithm in the least squares method was used in three steps: 1) measurement models goodness-of-fit 2) structural model goodness-of-fit 3) general model goodness-of-fit such that, first the accuracy of the relationships was ensured in the measurement models using the reliability and validity criteria and then the relationships in the structural part were examined and ultimately the overall model goodness-of-fit was examined.

Measurement models goodness-of-fit

Measurement models goodness-of-fit involves examining the reliability of research instruments. The reliability of the test depends on the accuracy of the measurement and its stability. Fornell and Larker suggest three criteria for evaluating the reliability of structures: a) the reliability of each item b) the

Composite reliability of each structure c) average variance extracted (AVE) [20].

Table 1: Demographic profile of the study participants.

	Characteristics	Frequency	Percent
Sex	Woman	113	56.5
	Man	87	43.5
Age	Under30	106	53.0
	30-40	57	28.5
	41-50	34	17.0
	Over 50	3	1.5
education degree	Bachelor	146	73.0
	Master	18	9.0
	MD	14	7.0
	Associate degree	12	6.0
	Diploma	8	4.0
	Specialist	2	1.0
education field	Nursing	38	19.0
	Health information technology	25	12.5
	Operating room science	25	12.5
	Laboratory science	21	10.5
	Radiology	20	10.0
	Physician	18	9.0
	Anaesthesia science	12	6.0
	Midwifery	10	5.0
	Medical emergency science	11	5.5
	Public health	4	2.0
	Optometry science	3	1.5
	HSE	1	0.5
	Environmental health	1	0.5
	Consultation technician	1	0.5
	Education physician	1	0.5
	Other	7	3.5
work history	Under 5 years	96	48.0
	5-10 years	26	13.0
	10-15 years	39	19.5
	Over 15 years	33	13.5

Reliability

To evaluate the reliability of the measurement model, factor load coefficients, Cronbach's alpha and Composite reliability were calculated as follows:

Factor load measurement: The reliability of each item refers to the amount of factor loads of each observed variable, and is used to determine the extent to which measurement indices (observed variables) are acceptable for measuring hidden variables. The minimum acceptable value is 0.3 and the factor loads are 0.4. Factor loads values higher than 0.5 indicate a strong level of significance and high correlation between the observed variables and the factor and also indicate that the structure is well defined [21]. Based on the results, all questions represented factor loads higher than 0.3 and thus were at an acceptable level.

Cronbach's Alpha

It is deemed as a classic well-known reliability measurement and an internal stability assessment index. Internal stability indicates the degree of correlation of a structure and its indices. In case of variables with a small number of questions, the alpha coefficient value of 0.6 is introduced as the coefficient limit and above 0.7 is an acceptable indicator of reliability [21]. As for the present research model, the alpha values are as follows: the diagnosis construct=0.786, follow-up=0.772, treatment=0.796, health care providers=0.704 and education=0.839 (Table 2).

Composite Reliability (CR)

To determine the reliability of each construct, the traditional Cronbach's alpha criterion is coupled with a more modern criterion of Composite reliability. In other words. The advantage of this criterion over Cronbach's alpha coefficient is that the reliability of constructs is not absolutely calculated and considers the correlation of their constructs with each other. Both criteria however are used to better measure the reliability. Composite reliability values above 0.7 for each construct indicate good internal stability for the measurement models and values less than 0.6 indicate no reliability, though [18]. Composite reliability values for the research constructs were obtained according to Table 2.

Homogeneous Reliability Coefficient (Rho A)

The Rho coefficient is also used to measure the internal reliability of constructs and is more reliable than Cronbach's alpha. The value of the coefficient should be more than 0.7, which was higher than 0.7 for all areas according to Table 2.

Structural model goodness-of-fit

According to the data analysis algorithm in the PLS method, the measurement models goodness-of-fit was followed with the structural model goodness-of-fit examination. Unlike measurement models in which the relationships between latent variables and observed variables are considered, the relationships among the latent variables are examined in the structural model and the criteria of significant t-value coefficients, r square or R^2, were examined the structural model goodness-of-fit purpose.

Table 2: The results of the study of the reliability of the variables and the explained variance of the partial least squares model of COVID-19 predictors

Constructs	Composite Reliability	Cronbachs	rho_A	R Square Adjust
Diagnosis	0.854	0.786	0.823	0.698
Treatment	0.858	0.796	0.811	0.658
Follow-up	.847	0.772	0.782	0.846
Education	0.892	0.839	0.848	0.742
Health Providers	0.803	0.704	0.780	0.656

T- values

To evaluate the structural model goodness-of-fit, several criteria are used, the first and most basic of which is the significance coefficients of Z or t-value. If the values of t are greater than 1.96, it indicates the correctness of the relationship between the constructs and thus confirms the research hypotheses at a 95% confidence level (Table 3).

Table 3: Structural model goodness-of-fit results

Constructs	T-values	Sig.
Diagnosis	19.837	<0.001
Treatment	18.304	<0.001
Follow-up	51.727	<0.001
Education	28.361	<0.001
Health Providers	19.596	<0.001

R square criterion (R^2)

The second necessary criterion for examining a structural model goodness-of-fit is to examine the coefficients of R^2 with respect to the latent variables of the model. According to the results (Table 2), they are higher than 0.6 for all areas. In other words, 0.67=significant, 0.33=moderate, 0.19=weak [19].

General Model goodness-of-Fit

Standardized Root Mean Square Residual (SRMR) is the root mean square of the residual squares calculated using the formula 2R2-1. The closer this criterion is to zero, the higher the goodness-of-fit of the model [18]. In the present study, this value was equal to -007.

Hypotheses Testing

According to the data analysis algorithm in PLS method, after examining measurement, structural and general models' goodness-of-fit, the load factor related to the paths of the research hypotheses is tested by examining the significant coefficients Z (t values) of each path and also the standardized coefficients. If the significance coefficient of each path is more than 1.96, the relevant path is confirmed at the 95% confidence level and the related hypothesis is confirmed, accordingly (Fig 2).

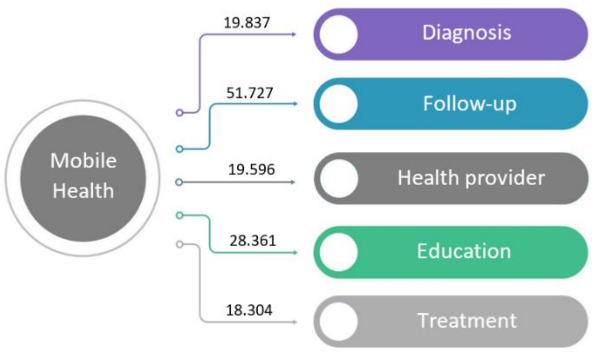

Fig 2: Final approved proposed model

DISCUSSION

The results showed that the highest role of m-Health apps concerning follow-up was 51.7% in pandemic management followed with education 28.3%, diagnosis 19.8%, health care providers 19.5% and treatment 18.3%. In other words, the results showed that the most effective area of m-Health apps in pandemic management is related to patient follow-up. The role of m-Health apps in monitoring patients and suspects at home was one of the most effective components regarding follow-up.

Many countries utilize m-Health apps as an effective strategy to track patients and suspects and monitor patient quarantine [21]. Contact tracing apps have been widely applied in countries such as China, South Korea, Singapore, and the United Kingdom in response to the COVID-19 pandemic [5]. In this way, this process includes collecting anonymous data to monitor the individual's movements and tracking confirm case cell phones to track suspected cases and their contacts. In some cases, these guides were individual and mandatory, while in some areas data was collected collectively and anonymously. In all of these cases, there was cooperation among the government, mobile network operators, and other data controllers, such as technology companies and financial service providers [21].

The education field was 28.3% effective in pandemic management and components such as providing self-care education to patients, preventive education and lifestyle training not only presented education but also greatly influenced other components confirming the potential of m-Health apps in educating people, patients, and suspects in pandemic management. Raising awareness and establishing online counseling through m-Health apps was one of the most widely used features of m-Health apps [22], which can inform and encourage people to take care of themselves and change their lifestyle without face-to-face meetings. Therefore, it can be considered as a powerful strategy for integration with health services [20].

Other areas had a relatively similar impact, though.

As far as diagnosis area was concerned, the m-Health apps could have distributed timely health information to the public and health care providers and referring those patients and suspects to the nearest care center.

The m-Health apps effectiveness concerning health care providers` pandemic management was 19.5% and the Ministry of Health recorded the highest impact among all components in introducing information resources and scientific applications. Other similar study, showed that the Mask app, introduced and supported by the Ministry of Health and government, was one of the most popular and widely used COVID-19 management apps in Iran [23]. However, one of the most important concerns regarding individuals' mobile phones data used for diagnostic processes was disclosure of individuals` confidential and identity information. To reduce these concerns, thus, anonymous data and individuals 'consent were guaranteed [21].

With regard to all the components, the reliability of information published on social networks and mobile apps about the pandemic presented the lowest score and hence showed the lack of trust of respondents to this type of information. In spite of high demand and potential benefits of mobile applications, there are limitations to their content quality control standards for consumers on the functionality and quality of applications. Therefore, m-Health apps offers both benefits and new challenges in the pandemic era. One of the most important limitations in this area is the dissemination of untrue and incorrect information and their non-compliance with medical guidelines, which can lead to misleading users [23]. Therefore, the organizations charge is supposed to effectively monitor the content of information published by apps, which is consistent with the results of the present study.

The lowest impact among all components of the research was treatment, which is based on e-visit-i-e-the ability to remotely arrange and visit the physician and the patient. Apparently, remote consulting and visit was the strategy many countries perused during the pandemic. The Indian Ministry of Health and Family Welfare has expanded the number of cases by expanding distance counseling guidelines [5]. Telehealth appointments were arranged for meeting between the health care provider and a new or previous patient using visual and auditory telecommunications. Audiovisual, secure text messaging, e-mail, or patient's portal, and electronic meeting (e-visit) communication linked a previous patient with the health care provider through the patient's online portal. Those applications' main purpose was to provide care and to support the patient and his family and reduce exposure to the disease in the pandemic period [24].

In contrast, mobile phones tools ability to treat COVID-19 patients without referring to care centers reported the lowest score, which showed the respondents' belief in visiting patients in person. The results of other studies showed that e-health in the pandemic period could not be an absolute care alternative but can be regarded as a complementary facilitator to improve communication between health care provider and patients [20, 25].

CONCLUSION

To the best of our knowledge, the present study is one of the first studies to model the role of m-Health in the COVID-19 pandemic management and therefore presents significant results for both health care policymakers and practitioners. According to the results, health policy makers will be able to influence the content of information published in m-Health tools, improve infrastructure, through m-Health tools in communicating with patients and practitioners could effectively communicate with patients, educate and monitor the situation through m-Health tools.

The present study can be a theoretical basis in developing models related to m-Health in pandemic management. Of course, the limitations of the present study were a limited number of variables and their direct influence on the pandemic management, which was related to the limited theoretical basis in this area. It is thus recommended that multiple variables and their relationships and impact on the final variable be investigated in future studies.

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Ethics approval (IR.ZAUMS.REC.1399.479) was obtained from the ethics committee of Zahedan University of Medical Sciences. Participation in the study was voluntary for all individuals and questionnaires were analyzed anonymously to maintain the confidentiality.

AUTHOR'S CONTRIBUTION

LE developed the study protocol, conducted data collection and drafted the manuscript. AY contributed to data analysis and edited the manuscript. AK assisted with data collection and contributed in the final manuscript edition.

All authors contributed to the literature review, design, data collection and analysis, drafting the manuscript, read and approved the final manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this study.

FINANCIAL DISCLOSURE

No financial interests related to the material of this manuscript have been declared.

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