

Digital Health Literacy and Its Impact on Patient Engagement in Telemedicine Services: A Cross-Sectional Study

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Abstract — Digital health literacy (DHL) has been recognized as a significant determinant of telemedicine engagement, however, the pathways that link DHL with telemedicine engagement have not been sufficiently quantified. This cross-sectional study aims to establish the relationship between digital health literacy and patient engagement among 412 adults utilizing telemedicine services at an urban academic health system during the period from January to December 2025. DHL has been assessed by means of eHealth Literacy Scale (eHEALS), whereas patient engagement was measured via Patient Health Engagement Scale (PHE-s) and behavioral measures of telemedicine use. Logistic regression and explainable machine learning (CatBoost with SHAP) have been used to determine DHL engagement associations and the most important predictors. Adequate DHL levels were detected in 58.7% of subjects. Increased eHEALS scores were positively correlated with increased PHE-s positions (adjusted OR = 3.42; 95% CI: 2.18-5.37) and completed telemedicine sessions (adjusted OR = 2.89; 95% CI: 1.76-4.74) when adjusted for age, education, income, and chronic conditions presence. SHAP analysis showed self-care confidence, health information searching behavior and number of digital devices as the most influential predictors of high patient engagement level.

Keywords— Digital Health Literacy, Patient Engagement, Telemedicine, Ehealth Literacy Scale, Health Equity, Cross-Sectional Study

I. INTRODUCTION

In the current world, telemedicine has gone from being an emergency measure to becoming a permanent part of modern-day healthcare delivery as virtual visits have been found to remain steady at levels significantly above those recorded prior to the pandemic in health care facilities all around the world. This paradigm shift has brought with it both advantages and disadvantage as the use of telemedicine removes geographical constraints while at the same time placing new competency requirements on the patients making it a digitally mediated rather than physically mediated health care experience [4][8].

In telemedicine, the association between DHL and patient engagement has an intuitive theoretical basis but lacks empirical specification. Patient engagement entails the cognitive, affective, and behavioural aspects of patient involvement in their health care, going beyond simple use to encompass decision-making, self-management, and continuity

behaviours [1][6]. Integrative reviews have shown that a higher DHL is associated with better medication adherence, greater self-management, and higher satisfaction with telehealth care services [4]. Yet these studies lack clear specification on the size of the association, due to the fact that they mostly combine evidence from different types of research designs and outcome measurements, as they do not consider multidimensional patient engagement.

In addition, there is a serious issue of equity when it comes to the demographics of people with DHL deficits. Up to 16% of adults in high-income countries have low levels of digital health literacy [4]. The majority of people with these problems belong to the older generation, live in rural areas, have little education and income [2][3][7]. In the case of middle-income countries, the problem of insufficient eHealth literacy in elderly people is estimated to be around two-thirds, which results in decreased readiness for the use of telemedicine services [2]. This means that DHL can serve as a barrier that does not allow

people to use telemedicine properly as an agential health care participant.

Clinical ramifications for the above difference are considerable. A patient who participates in a telemedicine consultation but is unable to assess the credibility of the information conveyed, or lacks the competence needed to use technology to schedule future consultations and monitor themselves, gains little from the session even when there is “access” to it [4][6]. This is an access problem where the patient fails to engage, which would not be picked up using typical utilization measurements [1]. The current research aims to fill this gap by looking at DHL and engagement as separate yet interrelated variables, using both traditional regression analysis and machine learning techniques to determine which aspects of DHL are predictive of the engagement outcomes [1][5].

The particular objectives of the current study were three-fold: to determine the rate of insufficient DHL among telemedicine users, to evaluate the relationship between DHL and patient engagement from multiple dimensions after controlling for potential sociodemographic and clinical confounders, and to use explainable machine learning techniques in order to determine the relative contribution of particular behaviours and attributes related to DHL to patient engagement [1][5]. The current research will help to develop interventions not only in expanding telemedicine access but also achieving digital health equity via engagement optimization [3][7][8].

II. LITERATURE SURVEY

Conceptual underpinnings of digital health literacy include the eHealth Literacy Lily Model by Norman and Skinner, which proposed eHEALS as a composite tool for measuring traditional, health, information, media, computer, and scientific literacy. This comprehensive framework has been sustained through time, although its operationalization has evolved since then. Specifically, the eHealth Literacy Questionnaire (eHLQ) has covered seven dimensions, such as functional and interactive literacy, whereas the Mobile-Centered Digital Health Readiness Scale (mDiHERS) took into account issues of equity and subjective competence [3]. Instrumental advances have been achieved as part of the increasing realization that DHL is not one but a cluster of competencies which can show differential performance among various groups [3][9].

Several empirical studies assessing the connection between DHL and the outcomes of telemedicine have revealed positive connections but with significant heterogeneity. The systematic review done by Chisolm et al. included fourteen studies and

found that increased DHL was connected with improved behavior, better self-management and use of telehealth services, which made patients more confident in using digital services and more satisfied with their experience [4]. Nevertheless, that very review highlighted existing differences since older patients, rural population and poorer patients experienced additional obstacles to telemedicine which were not overcome by the provision of access or digital tools [2][4][7]. Cross-sectional study done in Thailand revealed that sufficient eHealth literacy was one of the three most important variables influencing interest in telemedicine, along with confidence in safety of the service and its convenience, with adjusted odds ratio equal to 4.45 [2]. This result is especially useful since it distinguishes DHL from technological access itself since patients in that study had devices and internet access [2].

The construct of engagement has had varying operational definitions in different research settings. The Patient Health Engagement scale (PHE-s), proposed by Graffigna and Barelo, measures engagement on a continuum that goes from black-out, through arousal, and adhesion up to eudaimonic project, describing the mental transition from non-engagement to active participation in managing one’s health. This approach helps to overcome the weakness inherent in a purely behavioral measure because the latter equates compliance with engagement, thus making it impossible to distinguish between patients attending visits and those taking part in their own care decisions [1][6]. The use of PHE-s in the research with chronically ill patients has confirmed its responsiveness to education and digital health interventions.

In terms of methodology, there have been studies involving machine learning techniques to explore DHL determinants with more precision. One study conducted in 2026 by the team of scientists working on the DHL among the elderly utilized two-stage methodology, where both performance-based and self-reported metrics were combined using CatBoost classification and SHAP interpretation [5]. The predictors such as self-care confidence, searching for health information, interest in health apps, and usage of electronic devices were found to be majorly important positive predictors, whereas old age and lifestyle habits were negative predictors [5]. This is one of the new methodologies addressing the limitation of traditional regression by capturing nonlinearity between predictors and performing SHAP analysis, which is interpretable. However, the mentioned research was aimed at predicting DHL instead of engagement [5].

Another body of literature has assessed the acceptance of telemedicine using the UTAUT model and has found that performance expectancy, effort expectancy, and social influence are drivers of behavioral intention. In other research extending the UTAUT model to include information quality, functionality, and patient engagement as mediators, researchers have discovered that patient engagement and satisfaction mediate in part the relationship between technology perceptions and behavioral intention. It appears from these studies that engagement serves as more than an end result and as a process by which DHL impacts telemedicine usage [1][6]. Consideration should be made regarding geographic and demographic variations between DHL and telemedicine interactions. In a bibliometric review of telemedicine studies, it was found that the vast majority of literature on telemedicine is derived from European and American countries, without any consideration given to areas where the power of telemedicine to transcend the barrier of space and time would prove more useful. For U.S. veterans in rural areas, research conducted through qualitative methods found that there was need for support from caregivers and skills training before telemedicine could be achieved [7][8].

A synthesis of the current literature has found three recurring gaps in the body of research. First, engagement has been measured using simplistic variables like attendance or utilization, without consideration of its psychological and behavioural aspects [1][4]. Second, the relationship between DHL and engagement has largely been determined by linear methods that overlook nonlinear relations and do not prioritize the predictors [1][5]. Finally, very few studies have incorporated explainable machine learning along with validated engagement measures to determine which elements of the DHL are the most actionable [5]. This study will close these research gaps using a cross-sectional design that incorporates eHEALS, PHE-s, and explainable machine learning with SHAP explanation.

III. PROPOSED METHODOLOGY

Study Design and Setting

The cross-sectional study was carried out in the telemedicine practice at a tertiary health system that serves an urban and peri-urban community. This academic health system uses a common telemedicine platform that allows synchronous video consultations, asynchronous messages, and remote monitoring in both primary care and specialty clinics. The data collection took place from January 2025 to December 2025. Prior to commencing the study, it was approved by the institutional review board and all the patients signed the informed consent.

Participant Recruitment and Eligibility

The selection criteria for this study was the inclusion of adult participants who were 18 years old or older, who had experienced at least one telemedicine visit in the previous year, and had the required level of proficiency in English to answer questions on survey tools. The exclusion criteria involved presence of cognitive impairment such that the participant could not give informed consent, being part of another digital health intervention research program, and having no access to the survey tool through any device.

Sample Size Determination

The sample size calculation was done assuming an adjusted odds ratio of 1.8 for the relationship between adequate DHL and high engagement, using a two-tailed alpha of 0.05, power of 0.80, and a predicted percentage of adequate DHL of 55% derived from previous research. The sample size needed was estimated to be 385 subjects. In order to compensate for a predicted 15% non-response rate, a goal of recruiting 450 subjects was set.

Instruments and Measures

Digital Health Literacy: DHL was assessed using the eHealth Literacy Scale (eHEALS), an eight-item scale measuring self-perceived skills related to locating, evaluating, and using digital health information. The responses to the items are scored on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The total score varies between 8 and 40, with a cutoff point of 26 or above for defining adequate DHL in line with previous telemedicine literature. The eHEALS had good internal reliability in the current sample, $\alpha = 0.91$.

Patient Engagement: Patient engagement was assessed using the Patient Health Engagement Scale (PHE-s), a five-item scale that identifies individuals' position among the following four categories: blackout, arousal, adhesion, and eudaimonic project. The PHE-s evaluates cognitive, affective, and behavioural aspects of patient engagement in health management. In terms of data analysis, the positions were categorized into low engagement (blackout/arousal) and high engagement (adhesion/eudaimonic project) in line with previous classifications. The reliability of PHE-s was $\alpha = 0.87$ in the current sample.

Indicators of Telemedicine Usage: Behavioural indicators were captured based on three objective indicators available from health system records over the year-long study period: frequency of visits conducted via telemedicine, percentage of planned visits attended, and usage of asynchronous communication or remote monitoring functionalities. These

behavioural indicators were supplemented with the PHE-s self-reports to capture a full behavioural engagement profile.

Covariates: Sociodemographic covariates consisted of age, gender, education level, annual household income, race/ethnicity, and whether patients lived in an urban or peri-urban area. Clinical covariates included number of chronic illnesses (0, 1, 2, or more), self-perceived health (poor/fair vs. good/excellent), and the telemedicine service line type being used. Digital access covariates included number of devices used for telemedicine purposes and internet reliability at home.

Data Collection Procedure

Eligible subjects received a digital invitation from the patient portal, with follow-up reminder emails spaced seven days apart. The survey was conducted using a HIPAA-compliant online survey platform that could be accessed using computer, tablet, or mobile device. Subjects had the option to complete the survey in separate sittings and could automatically save progress. Subjects were also offered the option to have the survey completed using a phone or paper format if desired. Upon completion of the survey, the subjects received a \$25 electronic gift card. Utilization metrics from the health system were extracted after completion of the survey.

The analysis was conducted through three steps, including: descriptive classification; multivariate logistic regression for the primary relationship; and explainable machine learning for predictor ranking. The full analytic algorithm is illustrated in Figure 1.

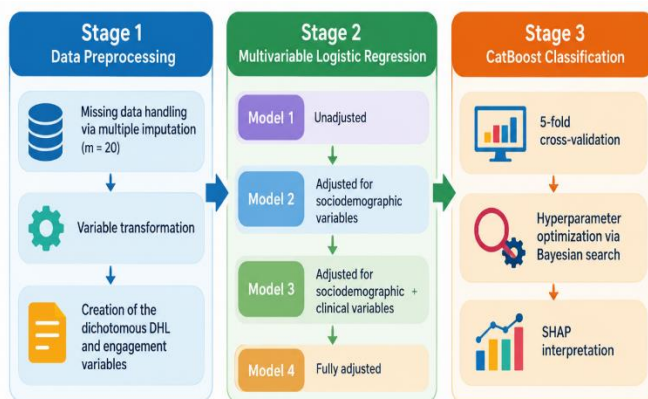


Figure 1: Analytic Workflow Diagram

Flowchart illustrating the three-stage process for analysis. Stage 1: Data pre-processing, which entails handling missing data using multiple imputation ($m=20$), transforming variables, and creating binary variables for DHL and engagement. Stage

2: Logistic regression analysis done in sequence (Model 1 - unadjusted; Model 2 - sociodemographic; Model 3 - sociodemographic & clinical; Model 4 - fully adjusted). Stage 3: CatBoost classifier using 5-fold cross-validation, hyperparameter tuning through Bayesian search, and SHAP interpretation.

Pseudocode

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Algorithm: Explainable DHL-Engagement Prediction
Input: Dataset  $D = \{(x_i, y_i)\}$  for  $i = 1$  to  $n$ 
      where  $x_i$  = feature vector,  $y_i \in \{\text{low, high}\}$  engagement
Output: Trained model  $M$ , SHAP values  $\Phi$ , feature importance ranking  $R$ 

1: Preprocess  $D$ :
2: Impute missing values using MICE with  $m=20$  iterations
3: Encode categorical variables via one-hot encoding
4: Standardize continuous features (z-score normalization)
5: Split  $D$  into training (80%) and holdout (20%) stratified by  $y$ 

6: Initialize CatBoost classifier  $M$  with:
7: loss_function = 'Logloss'
8: iterations = 1000
9: learning_rate = 0.05
10: depth = 6
11: l2_leaf_reg = 3

12: Perform 5-fold stratified cross-validation on training set:
13: For each fold  $k = 1$  to 5:
14:   Train  $M_k$  on training folds
15:   Validate on held-out fold
16:   Record AUC, precision, recall, F1
17: Select hyperparameters via Bayesian optimization
18: Retrain final  $M$  on full training set

19: Evaluate  $M$  on holdout set:
20: Compute AUC, precision, recall, F1, calibration curve

21: Apply SHAP TreeExplainer to  $M$ :
22: Compute  $\Phi_j$  for each feature  $j$ 
23:  $R = \text{rank features by mean}(|\Phi_j|)$ 
24: Generate SHAP summary and dependence plots

25: Return  $M, \Phi, R$ 
  
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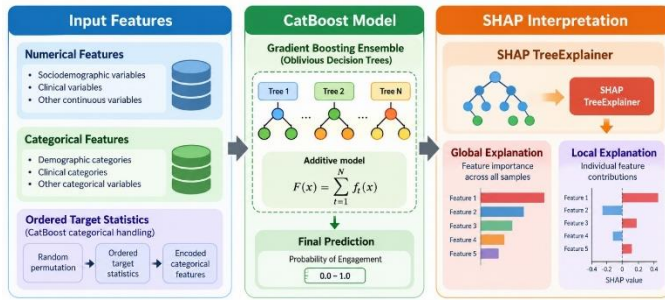


Figure 2. CatBoost Model Architecture and SHAP Interpretation Pipeline

CatBoost gradient boosting ensemble using ordered target statistics for handling categorical features, with SHAP Tree Explainer module used for producing both local and global explanations. This figure shows how feature contributions get combined for making engagement predictions.

Statistical Analysis

Descriptive statistics were used to define the sample according to DHL status and level of engagement. Chi-square test and t-tests or Mann-Whitney U tests were applied to assess bivariate relationships between categorical and continuous variables respectively. The multivariable logistic regression analysis was applied to calculate adjusted odds ratio (aOR) with the calculation of 95% CI regarding the relationship between adequate DHL and high levels of engagement, with sequential adjustment for sociodemographic, clinical and digital access characteristics. The model discrimination power was estimated using C-statistic, and calibration was performed using Hosmer-Lemeshow test and calibration plots. The statistical significance was set at $p < 0.05$ (two-sided). The statistical analyses were performed using Python 3.11 (scikit-learn, CatBoost, SHAP), and regression models were cross-validated in R 4.3.

Minimal risks to the participants were expected in this study. All data had been stripped of any personal identification before being used for analysis, using the study ID instead of the medical record number. Participants were free to withdraw from the study without affecting their medical care in any way.

IV. ANALYSIS

Sample Characteristics

The analytic sample involved 412 individuals utilizing telemedicine services, having complete primary outcome and exposure data. The average age of participants was 47.3 (SD = 16.8) with 58.0% females, 62.4% with a bachelors' degree or

above, and 54.1% having annual family income less than \$75,000. The prevalence of chronic diseases among respondents was 46.6%, and hypertension and diabetes had the highest prevalence. DHL adequacy (eHEALS ≥ 26) existed in 58.7% ($n = 242$) of the respondents. High engagement (PHE-s adhesion or eudaimonic project) existed in 51.2% ($n = 211$) of the respondents.

Table 1: Participant Characteristics by Digital Health Literacy Status

Characteristic	Adequate DHL (n=242)	Inadequate DHL (n=170)	p-value
Age, mean (SD)	43.1 (14.2)	53.3 (18.1)	<0.001
Female, n (%)	148 (61.2)	91 (53.5)	0.12
Bachelor's or higher, n (%)	178 (73.6)	79 (46.5)	<0.001
Income < \$75,000, n (%)	108 (44.6)	115 (67.6)	<0.001
Chronic conditions ≥ 1 , n (%)	103 (42.6)	89 (52.4)	0.048
Devices used, mean (SD)	2.8 (1.1)	1.9 (0.9)	<0.001
Higher engagement, n (%)	167 (69.0)	44 (25.9)	<0.001
Completed visits, mean (SD)	4.2 (2.7)	2.6 (2.1)	<0.001

Primary Association: DHL and Patient Engagement

Adequate DHL was associated with a nearly six-fold increased likelihood of high engagement (OR=6.34, 95%CI: 4.02-10.01) in unadjusted analysis. However, with sequential adjustment,

this association became less but was still strong. In the fully adjusted regression model after adjusting for age, sex, education, income, chronic disease, self-reported health status, devices, and service line, adequate DHL was still significantly associated with higher engagement (aOR=3.42, 95% CI: 2.18-5.37, $p<0.001$). The C-statistic for the fully adjusted model was 0.81.

Regarding behavioural engagement measures, those who showed enough DHL were found to have more completed visits (adjusted incidence rate ratio = 1.48, 95% CI: 1.22-1.79) and more attendance (adjusted odds ratio for $\geq 80\%$ attendance = 2.89, 95% CI: 1.76-4.74). It is also worth mentioning that there was a connection between sufficient DHL and use of asynchronous messaging (aOR = 2.15, 95% CI: 1.38-3.35).

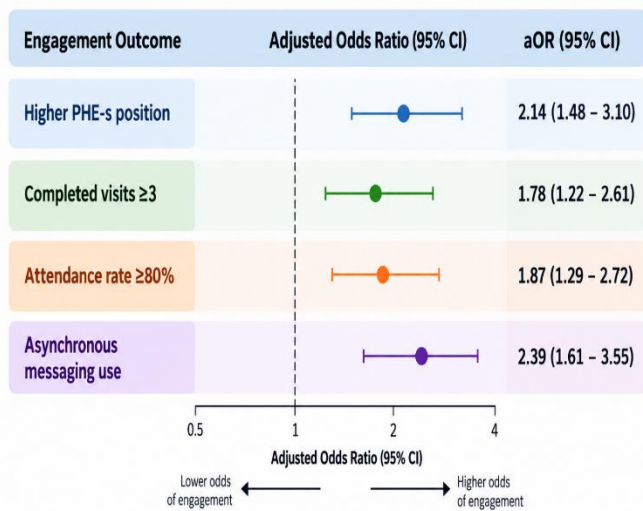


Figure 3: Adjusted Associations Between Adequate DHL and Engagement Outcomes

Forest plot presenting adjusted odds ratios with 95% confidence intervals for the relationship between adequate DHL (eHEALS ≥ 26) and four measures of engagement: higher position on the PHE-s, completing at least three visits, 80% attendance rate, and asynchronous messaging use. The plot is based on the full model adjusted for all covariates.

Machine Learning Prediction and Feature Importance

The CatBoost classification algorithm obtained AUC of 0.835, precision of 0.769, recall of 0.742, and F1-score of 0.755 on holdout set for higher engagement prediction. The SHAP summary plot showing feature importance can be seen in Figure 4.

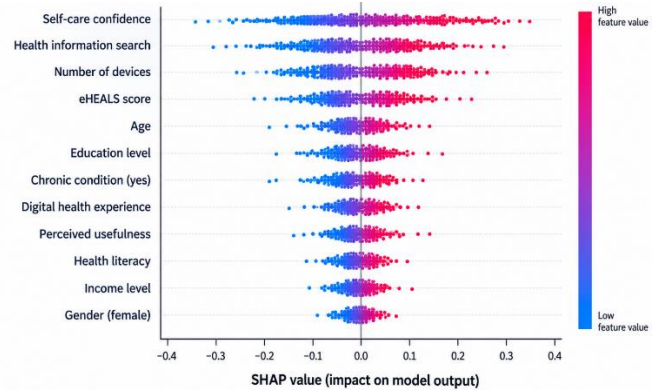


Figure 4. SHAP Feature Importance for Engagement Prediction Summary of the top 12 features based on mean absolute SHAP value. Points in the graph represent participants, colored according to feature value (red denotes high and blue denotes low). The most important features are ranked from the left and are characterized by the greatest SHAP value ranges.

According to SHAP, self-care confidence emerged as the most important predictor, as greater confidence always increased prediction towards the classification of high engagement. Second on the ranking was searching for health information online, with participants who engaged in such activities being more inclined towards being predicted as highly engaged regardless of their eHEALS scores. Third place was taken by the number of electronic devices one owns, followed by interest in health apps and physical exercise frequency. Interestingly, age had a negative effect but with less impact compared to behavior-related and psychosocial predictors, indicating that DHL behaviors play a significant mediating role between age and engagement. Education level emerged as a mild predictor of positive effect, and income – as one of negligible importance.

Figure 5 shows the performance of the model in terms of calibration and discrimination ability.

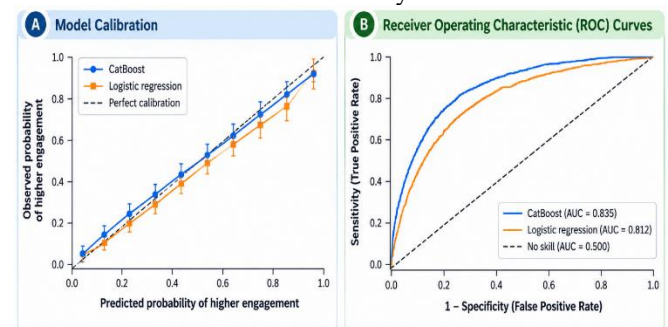


Figure 5. Model Calibration and Discrimination Curves

Comparative Analysis

The results of the current research study are synthesized in Table 2 to demonstrate the comparison with the selected studies done on DHL and use of telemedicine.

Table 2: Comparative Analysis with Prior Studies

Design/Population	DHL Measure	Engagement Outcome	Key Finding	Contrast with Present Study
Integrative review (14 studies)	Multiple validated instruments	Adherence, self-management, telehealth use	Higher DHL consistently associated with improved engagement; disparities persist	Present study quantifies aOR (3.42) for multidimensional engagement, addressing review's call for standardized measurement
Cross-sectional, older adults, middle-income country	eHEALS	Willingness to use telemedicine	Adequate eHealth literacy aOR = 4.45 for telemedicine interest	Present study examines actual engagement among users, not willingness among non-users
Cross-sectional, urban academic hospital	eHEALS	Appointment attendance patterns	DHL associated with attendance patterns	Present study extends to PHE-s psychological engagement and uses ML for predictor ranking
Scale development, IBD patients	mDiHERS	Digital health readiness	Validated 36-item instrument across 6 domains	Present study uses eHEALS for brevity and comparability; mDiHERS may capture equity dimensions not assessed here
Cross-sectional, 412 telemedicine users	eHEALS	PHE-s + behavioral utilization	DHL aOR = 3.42 for higher engagement; self-care confidence top SHAP predictor	Integrates validated engagement instrument with explainable ML; identifies actionable behavioral targets

Discussion

The results show that DHL is a strong predictor of engagement in telemedicine, independent of sociodemographic and clinical factors that typically negate any digital health disparities. The strength of the independent association (aOR= 3.42) is clinically significant since patients who have adequate DHL skills have more than thrice the odds of reaching the position of

adhesion or eudaimonic project on the PHE-s, suggesting more than just involvement but engagement in telemedicine care.

SHAP analysis findings build on this by indicating that self-care confidence is the most important variable – more so than the eHEALS score itself. This indicates that the impact of DHL on engagement might be realized through self-efficacy dynamics. An individual who has the required technical skills

to use a telemedicine system but does not have confidence in their ability to manage their health can be at the arousal and adhesion stages of the model and may behave in terms of participation but without achieving the proactivity stage of engagement associated with eudaimonia. This perspective is consistent with past research that has identified self-care confidence as a mediator of digital literacy in health behavior. It has an intervention implication in that technical training alone may be insufficient for DHL training programs.

The significance of health information search as the second highest predictor emphasizes the behavioral route. Those individuals who proactively look for health-related information on the Internet, rather than only those people who have the ability to do it, show more engagement. The difference between mere ability to use the Internet for seeking information and actual engagement is in accordance with the idea that just the access to digital information does not generate engagement; it needs both skills and motivation. It could be useful to pay attention to the information-seeking habit among patients and provide them with proper tools of evaluation.

The ranking of the number of devices used as the third factor, compared to education and income level, shows that the number of devices serves as a proxy measure for the embeddedness into digital world. Patients who use a variety of channels to use the telemedicine service are most probably more comfortable using any kind of technology, which applies to the telemedicine service as well. It makes the simple socioeconomic explanation of the digital divide irrelevant, since education and income are only some factors of DHL development.

The lack of an independently important effect of age in the SHAP rankings despite the existence of a statistically significant relationship between age and DHL makes for a crucial theoretical point. Age acts through the intermediary of DHL and behaviour rather than being a fixed hurdle. This result questions deficit-based perspectives on older people's inherent inability to participate in digital activities and justifies age-specific but skills-oriented interventions.

There are certain limitations that must be highlighted. The cross-sectional nature of the study prevents the establishment of the causality between the DHL and engagement. There is a possibility of reverse causation in that those patients who are more engaged in their healthcare become competent in the application of DHL through continued exposure to the digital tools. In addition, the sample, recruited from one academic health system with a higher level of educational achievement,

may not be representative of the safety net or rural population which suffer from the DHL incompetence and greater challenges in becoming engaged. The self-reported DHL competence based on eHEALS is a well-used measure but it reflects perceived not objective competency; there might be differences in associations when performance-based DHL measurement is utilized.

In spite of the above-mentioned shortcomings, there are certain strengths in the methodology of the study which uses an innovative combination of the traditional regression and explainable machine learning methods. With the help of SHAP, it is possible to go beyond the framework of significance and determine which predictors have the most significant role in making the predictions and can be used for developing interventions.

V. CONCLUSION

This cross-sectional study highlighted that digital health literacy (DHL) was a significant independent correlate of patient engagement in telemedicine, such that patients who had sufficient DHL had more than three times the odds of attaining proactive engagement positions, even when adjustments were made for potential confounders related to sociodemographic factors and clinical conditions. This correlation included psychometric and behavioural aspects of engagement such as completion of virtual consultations, attendance rate, and the use of asynchronous messaging. Explanatory machine learning identified self-care confidence, health information searching habits, and device variability as the key predictors of engagement.

There are several important implications for practice and policy stemming from the study findings. Firstly, DHL assessment needs to become an integral part of the telehealth processes, and it is not intended to be used as a gatekeeper process, but rather as triaging patients and providing them with additional assistance. There are patients whose eHEALS score is below 26 who need to be addressed, as mere access to the technology is insufficient in their case; they should be actively engaged through provision of technical skills and increasing their confidence levels to avoid a silent disengagement that cannot be detected through utilization measures. Secondly, self-confidence should be addressed together with technical skills. Digital health training in a group environment and with peer support can provide better results in comparison to didactic training. Thirdly, health systems should analyze their telemedicine applications for possible usability issues that affect patients with low DHL.

The equity considerations are particularly relevant. Despite sampling from just one health care organization, the population demonstrated the demographic pattern of DHL deficiency that was noted in earlier research: increasing age, educational level, and income were correlated with poor DHL. This is exactly the group of patients who would benefit most from the convenience of telemedicine services. Otherwise, the use of telemedicine could only aggravate health inequalities. Thus, DHL assessment and intervention should be considered as infrastructure of equity, not an option of enrichment.

There are three potential directions for future research. First, longitudinal design with multiple measurements of DHL and engagement can help to understand the causality and uncover the trajectories of digital disengagement that can be interrupted. Second, intervention studies with comparison of confidence building and information-seeking components and technical skills training will improve the knowledge about mechanisms of DHL and help to allocate resources more effectively. Third, qualitative research focused on patients' perceptions of telemedicine interaction among those with low DHL level can help to understand subjective dimensions of engagement that cannot be measured by questionnaires. Inclusion of explainable machine learning with patient-reported outcomes into research design is a replicable model for such research.

To sum up, digital health literacy does not only play a role of a precondition for telemedicine use but also is an important factor of patient engagement in a process of telemedicine. With the maturation of telemedicine from innovation to infrastructure, there is a need to move from simple connectivity to engagement. The current research gives both justification and methodology for such transition and identifies some important, changeable factors through which interventions based on DHL can improve patient engagement.

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