RESEARCH ARTICLE

Health literacy and patient activation among adults with chronic diseases in Singapore: A cross-sectional study

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Abstract

Aims: Increased patient activation levels can improve health outcomes. Hence, this study aims to examine the relationships between sociodemographic variables and domain-specific health literacies with patient activation.

Design: A cross-sectional design.

Methods: 200 outpatient adults with chronic diseases completed a survey that assessed their domain-specific health literacy and patient activation levels. Univariate and multivariate analysis of the variables were conducted on patient activation with 95% confidence interval (CI).

Results: Multiple linear regression analyses observed a positive linear relationship between the following domain-specific health literacy variables—"actively manage my health" ($p < .0001$, 95% CI: 0.89–2.29), "understanding health information" ($p = .008$, 95% CI: 0.28–1.85), and "finding good health information" ($p = .02$, 95% CI 0.13–1.51) with patient activation. The other sociodemographic and clinical variables were not statistically significant. Increased focus from healthcare professionals is needed on helping patients better find and understand health information and encouraging them to actively manage their health; elements which would raise their activation levels.

KEYWORDS
chronic diseases, health activation, health literacy, nursing, patient activation, patient education

1 | INTRODUCTION

Chronic diseases dominate the burden of diseases globally and are expected to continue to rise exponentially. From 2009–2017, the proportion of older adults with three or more chronic diseases in Singapore has nearly doubled (Choo, 2019). The consequences of chronic disease are manifold, ranging from increased medical expenditure, loss of productivity and income, decreased quality of life, a shrinking workforce due to higher morbidity and mortality rates, loss of gross domestic product and greater healthcare spending by the government (Murray et al., 2015).

In response, healthcare policies and practices have evolved to place greater emphasis on patients to have patient activation for self-management, activating patients to better manage their chronic diseases, due to the resultant clinical and healthcare utilization benefits. Patient activation is defined as an individual's

ability to acquire the necessary information, skills and confidence central to self-care (Hibbard et al., 2004). Higher patient activation levels have been linked to better self-care behaviours (Hibbard et al., 2004). Clinically, improved self-care behaviours have been linked to improvements in blood pressure, lipoprotein blood levels, blood sugar, and body mass index levels (Greene & Hibbard, 2012; Terry et al., 2011). Hence, it is essential to better understand the state of patient activation and predictors of activation in patients with chronic diseases.

2 | BACKGROUND

Patient activation has been shown to be multifactorial, linked to several sociodemographic and clinical factors as well as health literacy.

2.1 | Sociodemographic and clinical factors

Previous studies have identified age, household income and education level of patients as potential predictors of patient activation. Lower patient activation was observed in older adults in the community (Gerber et al., 2011). In contrast, higher patient activation was found among higher income earners and corresponded with increasing level of education (Dunlay et al., 2017; Sheikh et al., 2016). Nonetheless, patient activation was also found to be negatively associated with greater comorbidity, with individuals without comorbidities reporting higher activation levels than individuals with comorbidities (Smith et al., 2013).

2.2 | Health literacy

We adopted Nutbeam's definition of health literacy, which highlights three main components—functional, communicative or interactive, and critical literacy (Nutbeam, 2008). eHealth literacy is the capacity of an individual to obtain, comprehend, evaluate and apply online information to address health issues (Norman & Skinner, 2006). Its resemblance to traditional health literacy supports eHealth literacy to be considered synonymously with health literacy.

The ability to read and write health information was found to be positively correlated with patient activation and a statistically significant predictor of patient activation for the following studies (Dunlay et al., 2017; Sheikh et al., 2016). Furthermore, it was shown that a health literacy intervention was able to increase people's patient activation levels (Wallace et al., 2009).

While previous studies have shown potential predictors of patient activation, they have typically only explored one aspect (i.e. sociodemographic variables, clinical factors of health literacy as a broad domain). Additionally, most of the studies were also conducted in Western countries, whose different cultural context may make the result less applicable to a multicultural and multiracial

Asian setting. Thus, research is needed to better understand the relationship between sociodemographic and clinical factors, and domain-specific health literacy with patient activation in an Asian setting.

3 | THE STUDY

3.1 | Aims

We aimed to examine the relationships between sociodemographic and domain-specific health literacy with patient activation.

3.2 | Design

We conducted a cross-sectional study in Singapore.

3.3 | Participants

We recruited 200 individuals from the specialist outpatient clinics of a tertiary hospital in Singapore, using convenience sampling. The specialist outpatient clinics consisted of the following disciplines: cardiology, endocrinology, gastroenterology and hepatology, general medicine, respiratory medicine and rheumatology. Data collection took place at these clinics as they hosted the target population of persons living with chronic diseases. Inclusion criteria were as follows: (a) age 21 years old and above, (b) diagnosed with at least one chronic disease, (c) under follow-up at one of the specialist outpatient clinics, and (d) able to converse in English or Mandarin. Participants were excluded if they had any visual, speech or hearing impairments despite the use of aids, clinical history of psychiatric disorders or was currently seeking psychiatric treatment, cognitive impairment or any terminal disease.

Based on our literature review, we identified 15 parameters in the full regression model. These parameters included 10 sociodemographic and clinical variables and five domain-specific health literacy variables. Using the approximation of a minimum of 10 observations per parameter, we sought a sample size of 200 participants.

3.4 | Data collection

Our data collection occurred between August–December 2017. After obtaining participants' willingness to participate, a study-specific questionnaire either in English or Mandarin language was given to them.

3.5 | Instruments

The questionnaire included the following:

3.5.1 | Sociodemographic and clinical factors

The ten variables included gender, age, ethnicity, level of education, marital status, employment status, monthly household income, housing and chronic diseases' diagnosis.

3.5.2 | Health Literacy Questionnaire (HLQ)

The HLQ was used to assess health literacy. Four of the nine HLQ scales were incorporated: (a) finding good health information (FHI), (b) appraising health information (AHI), (c) understanding health information (UHI) and (d) actively managing one's health (AMH) (Osborne et al., 2013). Each item in AHI and AMH is rated on a four-point Likert scale ranging from one (strongly disagree) to four (strongly agree), while each item in FHI and UHI is rated on a five-point Likert scale ranging from one (cannot do or always difficult) to five (always easy). The four selected subscales were specifically chosen because they could holistically capture Nutbeam's definition of health literacy: functional, critical and interactive health literacies. A similar study in Singapore used the same four selected subscales in their study to test the influence of health literacy on health information behaviours (Suri et al., 2016).

3.5.3 | eHealth literacy scale (eHEALS)

The eHEALS was used to measure respondents' perceived skills at using information technology for health and determining the fit between eHealth programmes and consumers (Norman & Skinner, 2006). Scored across a five-point Likert scale from one (strongly disagree) to five (strongly agree), a score of 26 and above out of 40 meant a high eHealth literacy and a score of below 26 meant a low eHealth literacy.

3.5.4 | Patient Activation Measure (PAM)

The PAM-13 was used to evaluate one's ability to self-manage their chronic disease through self-reported knowledge, skills and confidence (Hibbard et al., 2004). PAM-13 was scored against a Guttman scale (1 = disagree strongly, 2 = disagree, 3 = agree, 4 = agree strongly and 5 = not applicable). The scores for this tool were then converted from the continuous Rasch item response theory logit scale to an overall activation score between 0–100 by Insignia Health. The PAM tool categorizes patients into four levels—level 1 (score ≤47.0), level 2 (score 47.1 to 55.1), level 3 (score 55.2 to 67.0) or level 4 (score ≥67.1), whereby a higher score reflects a more activated patient (Hibbard et al., 2004).

3.6 | Data analysis

Statistical analyses were conducted using R. Univariate analysis of each sociodemographic, clinical and health literacy variable against PAM was conducted. Variables that were found to be statistically significant ($p < .05$) were identified for fitting into a multivariate model. No interaction terms were identified in the multivariate model.

While this is an exploratory study, we decided to identify the multivariable model with the best overall fit as well. Backwards elimination was conducted to identify the most parsimonious model. Adjusted R^2 and overall F-test values were used to identify the model with the overall "best fit." We then applied an automatic stepwise regression using the Akaike information criterion (AIC) as a measure of fit. Both models were then compared to confirm if the both the backwards elimination and stepwise regression approaches identified the most suitable model (Venables & Ripley, 2002).

3.7 | Validity and reliability

Initial validation of HLQ showed a strong construct validity, reliability and high acceptability among adults who engaged in health care. The composite reliability scores of the HLQ-English were 0.86 (AMH), 0.77 (AHI), 0.89 (FHI) and 0.88 (UHI), reflecting strong reliability of the HLQ-English subscales used (Osborne et al., 2013). This strong reliability was also reflected in Singaporean settings when tested on college-going adults, wherein the Cronbach-α values of the different subscales in HLQ were found to be 0.82 (AMH), 0.17 (AHI), 0.81 (FHI) and 0.72 (UHI) (Suri et al., 2016).

Similarly, the HLQ-Chinese was found to have an excellent reliability of $\alpha = 0.947$ when tested for use on medical students in Chongqing, China (Zhang et al., 2016).

Psychometric properties of the eHEALS-English have previously been established with good internal consistency ($\alpha = 0.88$) (Norman & Skinner, 2006). Similarly, the psychometric properties eHEALS-Chinese yielded an excellent internal consistency ($\alpha = 0.92$) (Koo et al., 2012). Though the psychometric properties of both languages were originally developed and validated among adolescents, an examination of eHEALS in American adults with chronic diseases demonstrated excellent internal consistency ($\alpha = 0.94$) and no concerns for collinearity among items ($r < 0.90$) (Chung & Nahm, 2015). Furthermore, another study conducted among younger Singaporean college-going adults found good internal consistency ($\alpha = 0.89$) (Suri et al., 2016).

Examination of the psychometric properties of PAM-13 revealed that it was both reliable and valid. PAM-13-English has a good internal consistency ($\alpha = 0.87$) among adults with multiple chronic diseases (Hibbard et al., 2004). Similarly, the PAM-13-Chinese had a good internal consistency ($\alpha = 0.84$) among patients with chronic diseases (Zhang et al., 2017). Our earlier study in the Singaporean inpatient setting used the PAM-13 in both English and Mandarin, and also reported a good internal consistency ($\alpha = 0.87$) (Chan et al, 2021).

Hence, the bed of previous research on the psychometric properties of both the English and Chinese versions of HLQ, eHEALS and PAM-13 suggests that they are suitable for use among Singaporean adults with chronic disease, our population of interest. Nevertheless,

TABLE 1 Socio-demographics and clinical disease profile of the Participants (N = 200)

Variable	N	%
Gender		
Male	112	56.0
Female	88	44.0
Age		
21–40 years old	36	18.0
41–50 years old	35	17.5
51–60 years old	48	24.0
61–70 years old	52	26.0
71 years old and above	29	14.5
Ethnicity		
Chinese	139	69.5
Malay	28	14.0
Indian	27	13.5
Others[a]	6	3.0
Marital status		
Single	46	23.0
Married	143	71.5
Divorced or widowed	11	5.5
Level of education		
Primary and below	41	20.5
Secondary	67	33.5
Post-secondary	44	22.0
University and above	48	24.0
Employment status		
Full-time	95	47.5
Part-time	18	9.0
Retired/Unemployed	68	34.0
Homemaker	19	9.5
Monthly household income		
<$2,000	103	51.5
$2,000–$4,999	49	24.5
$5,000–$9,999	34	17.0
≥$10,000	14	7.0
Housing		
One- and two-room flats	18	9.0
Three- and four-room flats	110	55.0
Five-room and executive flats	41	20.5
Condominium and landed properties	31	15.5
Chronic diseases[b]		
Asthma and COPD	42	21
Diabetes Mellitus	74	37.0
Hypertension	91	45.5
Lipid disorders	56	28.0

(Continues)

TABLE 1 (Continued)

Variable	N	%
Others[c]	56	28.0
Comorbidities		
One	117	58.5
Two	49	24.5
Three or more	34	17.0

[a]Other ethnicities mentioned were Pakistani, Sikh and Caucasian.
[b]Participants can select more than one chronic disease. Thus, percentages do not add up to 100%.
[c]This includes rheumatoid arthritis, hypothyroidisms cases and kidney diseases.

we tested face validity of both the English and Chinese versions of the HLQ, eHEALS and PAM-13 in our clinical setting on four nurses and five patients independently to ascertain the ease of understanding of the items. Feedback was positive that items were understandable.

4 | ETHICS

This study was approved by National Health Group—Domain Specific Review Board (Reference number: 2017/00771). In view of the minimal risk of the study, only verbal consent was required.

5 | RESULTS

5.1 | Characteristics of the participants

A total of 276 potential participants were approached, 200 (72.7%) of whom consented to participate in the survey. There were no missing data. The characteristics of the participants are shown in Table 1.

The majority of the participants were males (n = 112, 56.0%), aged 51 to 70 years old (50.0%), with Chinese ethnicity (69.5%). Most participants reported a minimum of a secondary-level education (64%) and earned an income of less than SGD2000 a month (51.5%).

The most commonly reported chronic disease was hypertension (45.5%), followed by diabetes mellitus (37.0%). The majority of participants (58.5%) had only one chronic disease, with only 34 (17%) of participants having three or more conditions.

The mean activation score was 58.8 (SD = 15.0). The highest scoring domain was UHI, with a mean score of 3.80 (SD = 0.60). In contrast, the lowest scoring domain was AHI with a mean score of 2.80 (SD = 0.60). The mean eHealth literacy score was 24.80 (SD = 8.60).

5.2 | Univariate analysis of variables against patient activation

A summary of the univariate analysis of all variables is shown in Table 2. Age, ethnicity, level of education, monthly household

TABLE 2 Univariate analysis of variables against PAM

Variable	b (SE)	t-value/F-value$_{DF}$	p
Domain-specific health literacy			
Appraising Health Information (AHI)	2.43 (0.34)	$t_{193} = 4.91$	<.0001
Actively Managing Health (AMH)[a]	2.76 (0.37)	$t_{193} = 7.36$	<.0001
Finding Health Information (FHI)[b]	2.14 (0.22)	$t_{193} = 9.71$	<.0001
Understanding Health Information (UHI)[c]	2.57 (0.30)	$t_{190} = 8.60$	<.0001
EHealth Literacy Scale (eHEALS)[d]	0.80 (0.11)	$t_{193} = 7.19$	<.0001
Gender			
Male	e	$t_{193} = -0.68$	.5
Female	−1.49 (2.20)		
Age			
21–40 years old	e	$F_{190} = 2.85$	.03
41–50 years old	−5.37 (3.58)		
51–60 years old	−7.25 (3.34)		
61–70 years old	−8.10 (3.26)		
71 years old and above	−11.85 (3.73)		
Ethnicity			
Chinese	e	$F_{191} = 2.86$	.04
Malay	2.51 (3.12)		
Indian	6.44 (3.17)		
Others	6.44 (3.17)		
Marital status			
Single	e	$F_{191} = 1.97$	.1
Married	−2.86 (2.59) _		
Divorced or widowed	−9.93 (5.10)		
Level of education			
Primary and below	e	$F_{191} = 8.89$	<.0001
Secondary	7.08 (2.89)		
Post-secondary	13.20 (3.18)		
University and above	14.23 (3.08)		
Employment status			
Full-time	e	$F_{191} = 0.37$	.8
Part-time	−1.57 (3.95)		
Retired/Unemployed	−2.37 (2.47)		
Homemaker	−2.55 (3.86)		
Monthly household income			
<$2,000	e	$F_{191} = 4.12$	.008
$2,000–$4,999	3.69 (2.63)		
$5,000–$9,999	10.34 (2.99)		
≥$10,000	4.37 (4.24)		
Housing			
One- and two-room flats	e	$F_{191} = 1.21$	0.3
Three- and four-room flats	0.03 (3.87)		
Five-room and executive flats	5.16 (4.33)		
Condominium and landed properties	2.71 (4.53)		

[a]Adjusted for UHI, FHI and eHEALS.
[b]Adjusted for AMH, UHI and eHEALS.
[c]Adjusted for AMH, FHI and eHEALS.
[d]Adjusted for AMH, UHI and FHI.
[e]Referent value.

TABLE 3 Comparison of multivariate models predicting PAM

Model	Variables										R^2	Adj R^2	% Change from Adj R^2 in full model	AIC	F-test	
	AHI	AMH	FHI	UHI	eHEALS	Gender	Age	Education	Ethnicity	Income					F-value	p-value
Full	AHI	AMH	FHI	UHI	eHEALS	Gender	Age	Education	Ethnicity	Income	.45	.39	–	1,540.31	$7.51_{19,175}$	<.0001
1	AHI	AMH	FHI	UHI	eHEALS	Gender		Education	Ethnicity	Income	.45	.40	2.56	1,532.86	$9.67_{15,179}$	<.0001
2	AHI	AMH	FHI	UHI	eHEALS	Gender		Education		Income	.45	.41	5.13	1,527.45	$12.2_{12,182}$	<.0001
3	AHI	AMH	FHI	UHI	eHEALS	Gender				Income	.45	.41	5.13	1,523.09	$16.23_{9,185}$	<.0001
4	AHI	AMH	FHI	UHI	eHEALS					Income	.44	.42	7.70	1,521.18	$18.34_{8,186}$	<.0001
5		AMH	FHI	UHI	eHEALS					Income	.44	.42	7.70	1,519.54	$20.98_{7,187}$	<.0001
6ᵃ		AMH	FHI	UHI	eHEALS						.43	.42	7.70	1,517.57	$35.58_{4,190}$	<.0001

ᵃModel 6 was also generated when automatic stepwise regression modelling was performed.

income, AHI, AMH, FHI, UHI and eHEALS were all independently associated with PAM.

5.3 | Multivariate analysis of variables against patient activation

All variables which were found to be independently associated with PAM were included in the full multivariable model. No collinearity was observed between variables ($r < 0.90$). We subsequently sought to investigate to identify the "best-fitting" model (Table 3).

Backwards elimination and automatic stepwise regression identified the multivariate model with the "best fit," with the variables AMH, FHI, UHI and eHEALS (adjusted $R^2 = 0.42$, $F_{4,190} = 35.58$, $p < .0001$, AIC = 1517.57). In the best-fitting model, three of the four variables were significantly associated with patient activation—AMH, UHI and FHI (Table 4).

There was very strong evidence of a positive linear relationship between AMH and patient activation ($t_{190} = 4.49$, $p < .0001$), with a 1.59-unit increase in patient activation score for each unit rise in AMH score (95% CI: 0.89 to 2.29) after adjusting for UHI, FHI and eHEALS.

There was strong evidence of a positive linear relationship between UHI and patient activation ($t_{190} = 2.26$, $p = .008$), with a 1.06-unit increase in patient activation score for each unit rise in UHI score (95% CI: 0.28 to 1.85) after adjusting for AMH, FHI and eHEALS.

There was evidence of a positive linear relationship between FHI and patient activation ($t_{190} = 2.34$, $p = .02$), with a 0.82-unit increase in patient activation score for each unit rise in FHI score (95% CI: 0.13 to 1.51) after adjusting for AMH, UHI and eHEALS.

6 | DISCUSSION

Our study explored the relationships between sociodemographic and domain-specific health literacy with patient activation among outpatient adults with chronic diseases in Singapore. Through this, we found that three health literacy domains, AMH, UHI and FHI, are associated with patient activation. This is a key finding in our study as it can guide the evolution of healthcare professionals' patient engagement process to better engage and equip them in the self-management of their conditions.

The mean activation score of participants in our study was 58.8 out of 100. This score is similar to other Singaporean studies on activation, one on the activation of hospitalized older adults and another among patients with cardiac conditions (Chan et al., 2021; Ngooi et al., 2017). Hence, our mean activation score could be reflective of a "baseline" activation level of individuals living with chronic disease in Singapore, a potential common level of individuals with chronic disease to guide clinicians.

Our multivariate regression found that the following health literacy domains: AMH, UHI and FHI were statistically significant

TABLE 4 Comparison of multivariate models predicting PAM

Variables	b (SE)	95% Confidence Interval	t-value_DF	p
Actively Managing Health (AMH)[a]	1.59 (0.35)	(0.89–2.29)	$t_{190} = 4.49$	<.0001
Understanding Health Information (UHI)[b]	1.06 (0.40)	(0.28–1.85)	$t_{190} = 2.66$	.008
Finding Health Information (FHI)[c]	0.82 (0.35)	(0.13–1.51)	$t_{190} = 2.34$	.02
EHealth Literacy Scale (eHEALS)[d]	0.23 (0.12)	(−0.01–0.48)	$t_{190} = 1.89$	.06

[a]Adjusted for UHI, FHI and eHEALS.
[b]Adjusted for AMH, FHI and eHEALS.
[c]Adjusted for AMH, UHI and eHEALS.
[d]Adjusted for AMH, UHI and FHI.

predictors to patient activation in persons with chronic disease in Singapore. This reinforces the findings of a systematic review on the effectiveness of patient-activating strategies on adults with type 2 diabetes, whereby strategies leaning heavily on AMH and UHI, such as content-driven activities to enhance patients' skills in self-care, increased both patient activation and their blood glucose levels (Bolen et al., 2014). Hence, interventions aimed at raising these three domains would increase patients' activation levels. A key point of interest was that AMH was the strongest predictor of patient activation. This could point efforts towards changing the healthcare engagement on helping patients engage and make shared decisions on their care; hallmarks of a high AMH-scoring individual.

The strong association between AMH and patient activation in individuals with chronic disease could be explained by individuals with raised AMH possessing the capability to effectively take ownership of their health. As a result, a patient with a high AMH would be motivated to gain the skills and knowledge necessary for effective self-management, reflecting the health behaviour of a person with high patient activation (Clochesy et al., 2015; Osborne et al., 2013). Healthcare professionals can help raise patients' AMH by guiding them in effective goal setting for self-care and establishing realistic strategies to attain them. For example, goal setting through motivational telephone calls and newsletters was found to be positively associated with health behaviour especially in fruits and vegetable intake (Paxton et al., 2012). Healthcare professionals such as nurses can be prepared for this new approach through communication skills training to better assess health literacy levels as part of goal-setting with their patients to better activate them to self-care effectively.

The association between UHI and patient activation could be explained by the high prevalence of patient education material being prepared in the form of written materials. Hence, patients with a high UHI, reflected in their capability for reading and understanding written health information, would be better-equipped in taking proactive management over their conditions (Osborne et al., 2013). However, to meet the needs of an increasing pool of patients with different educational backgrounds and information needs, healthcare professionals can explore moving towards a combination

of didactic teaching and hands-on activities to better engage and empower them appropriately (Colledge et al., 2008). Patients can perform return demonstration or repeat key information delivered by healthcare professionals after their consultations to show their understanding. Being heavily involved in patient education, nurses can then ensure any misconceptions are immediately rectified, and understanding checked. Although it may seem time-consuming to perform this "teach-back" method, teach-back has been shown to not increase the length of consultations (Schillinger et al., 2003). The resultant provision of a greater understanding of health information through such strategies would empower patients to be more activated and obtain better health outcomes.

The association between FHI patient activation could be linked to high-FHI individuals having the awareness and skills to find and prioritize the information essential to better care for themselves (Osborne et al., 2013). Hence, patients can be taught where to find reliable health information from several sources especially the internet in our digitalized world. This has vast implications for nurses, who will have to empower patients in finding appropriate health information from trusted sources. One potential resource is evidence-based repositories of patient information such as UpToDate for patients (UpToDate, 2020). Such repositories give all the essential information patients would need to better care for themselves, saving the time that would have been consumed seeking information from individual websites and sources.

Sociodemographic variables such as age, household income and education level were not associated with patient activation. This could be because our sample consisted of younger patients with a lower educational background and income level than other studies of older persons that found these attributes to contribute towards patient activation (Gerber et al., 2011; Lubetkin et al., 2010; Smith et al., 2015). However, the profile of our patients matched that of a national study of older persons in Singapore (Teh et al., 2018). This shows that these sociodemographic variables, while important in guiding the relationship between patients and healthcare professionals, do not have an effect on patients' activation levels when compared to their health literacy, in particular their AMH, UHI and FHI.

Upon discharge from hospital, many patients are faced with the daunting task to care for themselves in the community. The findings from our study can guide healthcare professionals to focus on domain-specific health literacy interventions, appropriate to their patient's level of proficiency to improve their patient activation.

6.1 | Strengths and limitations

A key strength of our study is that our participants are representative of the general adult population who suffered from chronic diseases as they were recruited from a wide spectrum of outpatient clinics specializing in different chronic diseases. Hence, the findings are generalizable, especially among countries with demographic similarities to Singapore. The use of the HLQ and eHEALS also allowed us to capture a wider perspective of health literacy and eHealth literacy, going beyond the assessment of functional health literacy as done in typical studies. There was also minimal missing data, helping to maintain statistical power, reduce biased estimates and ensure conclusions drawn were representative and valid.

However, there are several limitations that need to be considered. The direction of association between variables cannot be ascertained in a cross-sectional study. The questionnaires used were self-reported and closed-ended questions; thus, it can only give the perceived skills and activation level of the participants. Further underlying reasons behind the health literacy and patient activation scores were also not explored or probed further. Therefore, more studies are required to explore the motivators and barriers influencing health literacy and patient activation.

7 | CONCLUSION

This study contributes to the growing literature in patient activation and health literacy. It has also laid the preliminary foundation for future chronic diseases self-management programmes. It found that AMH, FHI and UHI were predictors of patient activation among outpatients with chronic diseases through multivariate regression. As chronic diseases continue to proliferate, helping patients to become more activated to better engage in self-care and management of their conditions remains paramount in the role of healthcare professionals. Healthcare professionals will need to tap onto the needs of different patient groups based on their domain-specific health literacy competencies to increase their patient activation levels. It is hoped that healthcare professionals can meet patients at wherever their health literacy skills and patient activation levels are and give them with the necessary support and information to attain improved health outcomes. These can in turn help to manage the chronic disease burden on the healthcare system by reducing the complications.

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