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The counterintuitive self-regulated learning behaviours of healthcare providers from low-income settings

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ABSTRACT

Self-regulated learning (SRL) is useful for understanding self-directed learning practices. However, SRL behaviours - despite being deemed highly context-dependent - remain mostly unexplored for healthcare workers in low-income countries. This study details how SRL strategies vary and impact on healthcare providers' learning gains when using digital learning platforms. We apply Latent Profile Analysis (LPA) to questionnaire responses from a sample of 264 healthcare providers, arguably the first time LPA has been applied for the context in this subject-domain. We identified four SRL profiles: *High, Above-Average with Low Help-Seeking, Average,* and *Low* SRL profiles with significant differences in SRL strategies between the four profiles confirmed by Kruskal-Wallis test and logistic regression. Healthcare providers with more specialised clinical training were most likely to be in the *Low* SRL profile, but compared to the other profiles, maximised possible learning gains in the fewest learning iterations. From our findings, SRL may not adequately represent the nature of the interaction between these learners and contextual characteristics. Exploring the important role of various external learning regulation behaviours that influence healthcare providers SRL might help address this shortcoming. These findings provide insights into the learner factors to consider when implementing technology-mediated learning in these resource-contexts. They also offer plausible future research directions into how to maximise healthcare providers' learning gains on digital platforms that is informed by how learners in low-income contexts regulate their self-directed learning.

1. Introduction

Countries in the Global South have more than 20% of the global disease burden and the most severe health workforce shortage; they account for 64% of the global health workforce shortage, with Sub-Saharan Africa being the hardest hit (M. Roser & Ritchie, 2019; WHO, 2016). The dire need for trained health workers is compounded by a severe lack of training opportunities and resources, which contributes to almost half of avoidable deaths globally (UNICEF, 2018; WHO, 2019). Mobile- and online-based learning have the potential to help address the training need in these regions, given their growing ubiquity and use for seeking information (Edgcombe, Paton, & English, 2016; Silver & Johnson, 2018). This is because face-to-face training is costly to resource-constrained individuals and

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institutions (Chaudhury et al., 2016). Furthermore, digital learning as a platform for clinical training is at least equal to the traditional approaches in improving learning outcomes (Car et al., 2019). However, because learning with mobile devices is typically individualistic and voluntary, self-directed learning is essential for developing understandings and meeting personal learning goals (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). Unlike structured face-to-face learning, learners using digital platforms determine the nature of engagement with and spaced repetition of, the study content (Kizilcec et al., 2017).

Despite digital learning platforms offering more valuable opportunities for self-directed learning in clinical training (Lee, 2015), and shown to produce a learning effect from self-directed learning that is equivalent to blended and face-to-face learning for training healthcare providers (George et al., 2019), a lot of learners grapple with self-directed learning on digital environments that offer low instructional support (Lajoie & Azevedo, 2006; Wong et al., 2019). Additionally, for a typical healthcare provider -who is the target learner in this context-digital learning is only a small slice of their day: they are already overworked, underpaid and under-resourced (Barteit et al., 2019; Couper et al., 2018). Therefore, any learning intervention should reflect their situated learning needs and address ways for enhancing engagement, inquiry and understanding. Such digital learning interventions also requires highly motivated self-directed learning from students to allow them to realise their objectives (Zheng, Rosson, Shih, & Carroll, 2015). In our context, this creates a challenge in providing support to healthcare providers to help them realise their learning objectives on digital learning environments because in general, we do not know what is going on from the learner's perspective. There is a scarcity of evidence from low-income countries (LICs) on digital learning platforms that account for the contextual situated learning needs of learners (such as individual healthcare providers) as the learners continue to gain knowledge through them (Bollinger et al., 2013; Car et al., 2019; Edgcombe et al., 2016).

In this study, we seek to explore how digital platforms might be implemented to support self-directed learning in a Global South context for continuous professional development. Our particular interest is in the self-regulation learning by healthcare providers from LICs on digital learning platforms. We are interested in characterising learners' efforts in controlling their learning behaviours, as underpinned by self-regulated learning (SRL) theory (Pintrich, 2000; Zimmerman, 2000). We investigated how SRL strategies influence knowledge gain and how they differ based on healthcare provider characteristics.

1.1. Self-regulated learning (SRL)

Self-regulation is a process that is initiated by learners to control their learning through: (1) using cognitive strategies to acquire, store, and retrieve of information (e.g., elaboration); (2) using metacognitive strategies to plan, monitor and regulate their learning process in order to accomplish a goal; (3) using resource management strategies to manage time, help, effort etc. when organising one's study (Pintrich, 2000). Feedback is considered the key mechanism for SRL behaviour where the generation and processing of internal feedback and external feedback respectively by learners are useful for monitoring engagement and attainment of their learning goals for specified learning tasks (Butler & Winne, 1995).

The SRL conceptualisation this study has taken follows Pintrich's model of SRL because it emphasises SRL tactics that are more amenable to better-refined quantitative evaluations (Rovers, Clarebout, Savelberg, de Bruin, & van Merriënboer, 2019). Despite its concerning treatment of SRL as a static stable trait (as opposed to a dynamic context-dependent process) which is a limitation, we argue that Pintrich's model is the only SRL-based model that seeks to comprehend the learner's attempt to overtly control their own learning behaviour (Panadero, 2017) and so is appropriate for this study.

This is in contrast to Zimmerman's model which conceptualises SRL as "self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals" (Zimmerman, 2000, pg. 14). We considered these two SRL models due to their established nature in pertinent literature. Given evidence from published literature on SRL on digital learning environments (Boud, 2013; Panadero, 2017; Schunk, 2005), strategies which are expected to enhance learning include:

(1) Goal setting: Framing of learning objectives so as to gauge the required effort needed to realise them (Schunk, 2005; Zimmerman, 2000);
(2) Strategic planning: The scheduled spacing and ordered accomplishment of learning tasks needed to realise learning goals (Zimmerman & Pons, 1986);
(3) Self-evaluation: Active monitoring and judging learner's own progress and performance against personal learning objectives (Boud, 2013; Schunk, 2005);
(4) Task strategy: Arrangement of study tasks and activities to ensure maximisation of learning process and outcomes and the effort used in learning (Effeney, Carroll, & Bahr, 2013; Richardson, Abraham, & Bond, 2012; Zimmerman & Pons, 1986);
(5) Elaboration: Establishing meaning from the learned knowledge concepts by combining new knowledge the learner gained with what they already knew (Niemi, Nevgi, & Virtanen, 2003; Weinstein, Acee, & Jung, 2011);
(6) Help seeking: Soliciting help from fellow students, informational resources or a tutor (Aleven, Mclaren, Roll, & Koedinger, 2006).

From research in high-income settings, we know that gaps remain in our understanding of the links between the above learning strategies and learning performance (Milligan & Littlejohn, 2016). When performance data is provided, it is linked to written examinations and is particularly susceptible to recall bias where survey instruments were rolled out in retrospect to a completed learning session (Cho, Marjadi, Langendyk, & Hu, 2017). However, the level of experience, instructional design mode (e.g. problem-based learning versus alternatives), the form of technological resources afforded to learners, and flexibility while pursuing learning needs, were positively associated with high SRL (Cho et al., 2017; Milligan & Littlejohn, 2016). In high-income settings, where SRL strategies have been factored into the design of instructional support for healthcare providers on digital learning platforms, significant learning gains have been shown (Feyzi-Behnagh et al., 2014). We are yet to come across primary research cognisant of LICs context that would provide a basis for supporting SRL strategies of healthcare providers using digital learning platforms. We assert that, if learning is socio-culturally situated and informed by context (Polly, Allman, Casto, & Norwood, 2017), then SRL research done in high income countries (which are almost all) – including those especially looking into clinical context (van Houten-Schat et al., 2018)- would arguably be limited in reflecting learning behaviours from the Global South. Previous studies in SRL corroborate this view (Barnard, Paton, & Lan, 2008; Zimmerman & Schunk, 2001, pg. 125) including recent evidence synthesis of global research on the use of digital learning platforms by healthcare providers (Car et al., 2019; Gentry et al., 2019).

The research questions in this study are:

(1) How do healthcare providers' SRL strategies manifest and vary by individual learner characteristics on digital learning platforms? and (2) What influence do these strategies have on healthcare providers' learning gains?

In answering these research questions, the broader contributions of this paper to the field are:

(1) Understanding SRL's behavioural expressions in digital learning platforms for a diverse healthcare provider population in low-income settings, which until now have remained mostly under-researched.
(2) Considerations of how the links between learning gains and SRL strategies may inform the targeted implementation of digital learning interventions for healthcare providers, such as adaptive instructional scaffolding.

2. Methods

2.1. Study context, participants, and procedure

In this context, there is not an active registry of healthcare providers from which we could derive a generalisable sample partly due to the lack of up-to-date administrative records of active healthcare providers (North, Shung-King, & Coetzee, 2019). The research study used two digital learning platforms, a popular regional online-learning computer-based platform (i.e. "Daktari-Online") and our openly-accessible Android-based gamified learning smartphone application for neonatal emergency care training (Life-saving Instructions For Emergencies (LIFE)) which we are beta-testing in (countries removed for blind review) currently Tuti et al. (2020). Both platforms are recognised by relevant clinical professional bodies and are currently being used by healthcare providers from East and Central Africa and South-East Asia regions. This was done to try to attain a context representative sample while reflecting the two most common self-directed digital learning platforms for clinical training in this context: mobile- and computer-based learning modes. The learning content are not massive open online courses; they are controlled by relevant healthcare regulatory bodies with their access targeting clinicians only. The use of these two exemplar platforms was to ensure (1) digital platforms used for learning are varied (mobile-vs. computer-based), (2) other low-income contexts apart from East Africa are represented (3) multiple content modalities are represented (i.e. gamified versus non-gamified), and, (4) different types of assessment is represented (i.e. formative versus summative). More details about these platforms is provided in the Supplementary material (Multimedia Component 1). In this study, the focus was on how individual healthcare providers perceived themselves to have overt control over their self-regulated learning on these two digital platforms, as opposed to how the platform features were designed to enhance SRL strategies. Such evaluations of platform features' effect on SRL strategies and outcomes are substantive in their own right. We have already embarked on such finer-grained evaluations, examples of which we have reported in detail elsewhere (Tuti et al., 2020).

Recruitment of survey respondents from Daktari Online was through a mailing list inviting healthcare providers who had used the platform to learn in the last one year to participate in the study. This was circulated after receiving the necessary ethical approval from the national medical research institutions. Participation was optional and data collected after the web-based informed consent process. Recruitment of survey respondents from LIFE participants occurred at the end of the learning sessions within the LIFE smartphone app and was optional. The LIFE app was publicised through snowballing recruitment of healthcare providers, using healthcare professional societies' official social media accounts, press release through national newspaper outlets, national clinical conferences and meetings, approaching national referral hospitals and clinical training schools. To be eligible for inclusion, healthcare providers had to be either in students in, or actively providing, clinical care. All participants included had engaged in online learning before participating in the survey. While the recruitment efforts were focused on reducing selection bias, because the final sample is based on voluntary self-selected participants, we cannot rule out voluntary response bias. This study, framed as a case-study underpinned by Self-Regulated Learning theory, follows the analytical and transferability model of generalisability (to context) as opposed to statistical generalisability (Polit & Beck, 2010).

The final study sample was 264, of whom 184 (69.70%) were recruited through LIFE, and 80 (30.30%) were recruited through Daktari Online. This consisted of participants from both public and private hospitals in low income settings such as East Africa and South East Asia; in clinical cadres such as nurses, clinical officers and medical doctors; and with experience levels varying from students to consultants. Data from these participants would aid in exploring SRL in LICs contexts for continuous professional development across clinical domains, and healthcare experience levels. This sample is not generalisable to healthcare providers from this region. But it is, by clinical cadre and practice level, arguably the most diverse exposition of SRL of healthcare providers in LICs providing insights to SRL's transferability to this context.

2.2. Study instruments, variables, and data management

Data was collected using an adapted validated Online SRL Questionnaire tool (OSRLQ) which demonstrated internal consistency of scale reliability for all SRL sub-components, as illustrated by Cronbach alpha score (Kizilcec et al., 2017; Tavakol & Dennick, 2011). It contains the *Goal setting, Strategic Learning, Task-Strategy, Elaboration, Self-Evaluation* and *Performance* sub-scales, with example questions for each sub-scale illustrated by Supplementary Table 1. This survey tool was preferred due to its inclusion of SRL measures that are based on established instruments and have been shown to have high reliability (Barnard, Lan, To, Paton, & Lai, 2009; Kizilcec et al., 2017; Littlejohn & Milligan, 2015). De-identified and anonymised data was stored on a privately secured Google Firebase database. Additional fields collected from healthcare providers included clinical cadre, clinical practice level, age and experience in years. Survey respondents using LIFE platform had additional learning data that included performance scores as a percentage. The study instrument had better than expected SRL composite Cronbach alpha of 0.986, compared to the validating study's 0.92, and an omega coefficient of 0.903 (which is more robust to the instrument's length than the Cronbach alpha), and a more appropriate measure of scale reliability (Dunn, Baguley, & Brunsden, 2014).

2.3. Statistical analysis

The initially planned analysis was Confirmatory Factor Analysis (CFA) of SRL, fitted in similar fashion to original study using the same instrument (Barnard et al., 2009). Assuming measurement invariance, CFA would be used to evaluate the how well the theorised SRL model fits LICs healthcare providers learning behaviours as captured by their survey responses. Significance tests provided for factor loading coefficients would also be used to characterise the individual SRL strategies influence on the hypothesised SRL model. Since the instrument item distributions were strongly skewed (Supplementary Table 1), Maximum Likelihood (ML) $\chi2$ goodness-of-fit test statistics would yield inflated estimates and underestimate parameter standard errors. We used Satorra-Bentler (SB) scaled $\chi2$ estimators and robust parameter standard errors to help correct for these biases and opted for Robust Maximum Likelihood estimator (MLR) to account for the non-normal skew at the indicator distribution tails (Supplementary Table 1).

For CFA model fit evaluation, we used Comparative Fit Index (CFI) ≥ 0.9, Tucker-Lewis index (TLI) ≥ 0.9, Root Mean Square Error of Approximation (RMSEA) < 0.06 and Standardized Root Mean Residual (SRMR) ≤ 0.06 for acceptance based on continuous measures (Hu & Bentler, 1999). If the CFA model performance thresholds were not met, we would use Latent Profile Analysis (LPA) (B. Muthén, 2004; B. O. Muthén, 2001; Pastor, Barron, Miller, & Davis, 2007) to identify healthcare providers latent SRL profiles. LPA is a technique that identifies groups of healthcare providers in the survey sample who had similar response patterns to the items in the SRL instrument. Within the identified latent profiles, healthcare providers belonging to a specific profile have a higher probability of sharing similar responses to the survey instrument compared to healthcare providers in other profiles. The procedure for fitting such models is explained in detail in published literature (B. Muthén, 2004; Stanley, Kellermanns, & Zellweger, 2017).

We fit the LPA models using maximum likelihood estimator approach in *Mplus* 7.4 to estimate model parameters (Pastor et al., 2007). The initial and final iterations were 4000 and 40 respectively, and they were settled upon in efforts to minimise structural

Table 1
SRL survey participants by platform.

Platform	Daktari Online	LIFE	All
	N (%)	N (%)	N (%)
Clinical Cadre			
Consultant (*Doctors whose practice requires training in a speciality area*)	26 (9.85%)	10 (3.79%)	36 (13.64%)
Medical Officer (*Doctors equivalent to "Junior Doctor" or GP cadres in the UK*)	49 (18.56%)	51 (19.32%)	100 (37.88%)
Clinical Officer (*A cadre commonly found in Sub-Saharan Africa*) *	4 (1.52%)	27 (10.23%)	31 (11.74%)
Nurse	0 (0%)	72 (27.27%)	72 (27.27%)
Other	1 (0.38%)	24 (9.09%)	25 (9.47%)
Clinical Level			
Active Practice (Not undergoing any training)	50 (18.94%)	112 (42.42%)	162 (61.36%)
Active Practice (Currently undergoing training)	24 (9.09%)	12 (4.55%)	36 (13.64%)
Student	1 (0.38%)	55 (20.83%)	56 (21.21%)
Other	5 (1.89%)	5 (1.89%)	10 (3.79%)
Age (in years)			
18–24	1 (0.38%)	43 (16.29%)	44 (16.67%)
25–34	34 (12.88%)	86 (32.58%)	120 (45.45%)
35–44	32 (12.12%)	34 (12.88%)	66 (25%)
45–54	6 (2.27%)	16 (6.06%)	22 (8.33%)
55–64	5 (1.89%)	1 (0.38%)	6 (2.27%)
65+	2 (0.76%)	0 (0%)	2 (0.76%)
Missing	0 (0%)	4 (1.52%)	4 (1.52%)
Experience (in years) **	10.98 (10.05)	6.92 (7.47)	8.15 (8.52)
All	80 (30.3%)	184 (69.7%)	264

Note: **Wilson, A., Lissauer, D., Thangaratinam, S., Khan, K. S., MacArthur, C., & Coomarasamy, A. (2011). A comparison of clinical officers with medical doctors on outcomes of caesarean section in the developing world: meta-analysis of controlled studies. Bmj, 342, d2600.*
***Experience in years provided as Mean (Standard Deviation).*

under-identification. While model fit statistics such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and [sample] adjusted BIC (aBIC) were used to provide an indication of whether increasing the number of latent profiles improved the model fit (Nylund, Asparouhov, & Muthén, 2007). However, to determine the final number of latent profiles to use, we used Lo-Mendel-Rubin (LMR) model comparison test with a cut-off p-value < 0.05, combined with Entropy cut-off probability of >0.8 (Nylund et al., 2007). Entropy is defined as the normalised measure of model-based classification accuracy, with higher values indicating more precise assignment of individuals to latent profiles; when used together with LMR test, it provides a more robust basis for LPA model comparison compared to AIC, BIC, and aBIC (Nylund et al., 2007).

To ensure replicability of findings from the LPA model, it was run using 20 randomly drawn samples of the participants to test where we could replicate the decision for the number of profiles selected. Logistic regression was conducted by using the profile membership as a dependent variable and demographic characteristics as possible predictor variables. We did this to explore how demographic characteristics were associated to the identified SRL profiles.

Given the violation of normality distribution in the instrument's variables (Supplementary Table 1), Kruskal–Wallis non-parametric test (Spurrier, 2003) was used to explore if there were statistically significant differences between the SRL strategies across the identified SRL profiles. We conducted post-hoc non-parametric pairwise Whitney-Mann-Wilcoxon tests (Fay & Proschan, 2010) drilling down to where possible differences may lie given that Kruskal-Wallis test would only give an indication of whether there is enough evidence to suggest that in a particular SRL skill, one or more SRL profiles is significantly different from another SRL profile, but no indication of which profile those may be or by how much (López, Valenzuela, Nussbaum, & Tsai, 2015).

3. Results

We report data collected between February 7, 2019 and July 31, 2019. Of the 264 participants, 184 (69.70%) were recruited through LIFE, and 80 (30.30%) were recruited through Daktari Online. The breakdown of demographic characteristics of the participants is provided in Table 1 with additional breakdown comparisons provided in Supplementary Table 2. Majority of respondents were medical officers -equivalent to junior doctors in UK- (N = 100, 37.9%), followed by nurses (N = 72, 27.3%). They were predominantly between 25 and 44 years of age (N = 186, 71.5%) and practicing health workers not undergoing any training (N = 162, 61.4%).

There were no survey responses from "Daktari-Online" users who were nurses and only one who was a student (Table 1). Clinical officers were more likely to be users of LIFE with Daktari-Online having on average, three more years of experience compared to LIFE users (Table 1).

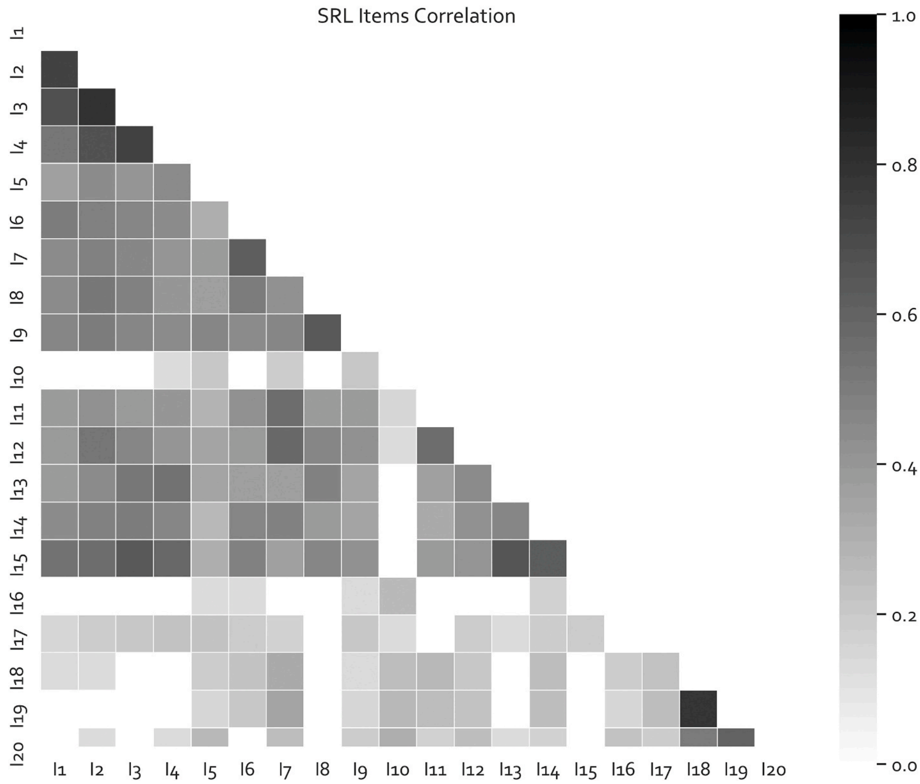

Fig. 1. SRL Item pairwise correlation representation. Items descriptions provided in Supplementary Table 1. Only statistically significant correlations are shaded.

Overall, the SRL questionnaire tool had high internal consistency, with a Cronbach alpha value of 0.986. This could be inferred by the moderate to strong correlations for almost all the sub-scales except for help-seeking sub-scale as illustrated in Fig. 1. However, the overall model fit for the original digital self-regulated learning scale was not satisfactory based on our outlined preferred thresholds (RMSEA = 0.078, SRMR = 0.079; CFI = 0.867, TLI = 0.845) which were poorer than the original study deriving the tool (RMSEA = 0.04, CFI = 0.96, TLI = 0.95) but better than the validating study's results (RMSEA = 0.081, CFI = 0.666) which modified the tool slightly (Jansen, Van Leeuwen, Janssen, Kester, & Kalz, 2017). Our poor CFA model fit statistics are in spite of our study having better composite and sub-scale Cronbach alpha scores (Barnard et al., 2009; Jansen et al., 2017; Kizilcec et al., 2017). Our CFA model fit's "*reliability paradox*" might be due to the small size of the sample used, but the paradox is a common issue identified in literature that does not yet have a clear resolution (McNeish, An, & Hancock, 2018). Further examination of the SRL components revealed strategic learning and task-strategy sub-scales to have particularly unsatisfactory RMSEA and TLI (Supplementary Table 1). Consequently, the rest of the analyses reported here focuses on latent profile analysis.

3.1. Model results from latent profile analysis (LPA)

Table 2 illustrates results from fitting LPA models which were implemented to identify the SRL profiles of healthcare providers from LICs. These latent profiles are meant to characterise how LICs healthcare providers' SRL strategies manifest on digital learning platforms. These model fit statistics are results from comparing a model with K profiles to a model with (K-1) profiles. The test statistic from Lo-Mendel-Rubin (LMR-LRT) indicates whether the model with K profiles is significantly better than the model with K-1 profiles. If it is lower than 0.05, the model with K profiles is preferred, otherwise, the model with K-1 profiles is preferred.

There was a consistent decrease in model deviance (log likelihood) with the increasing number of profiles up until four profiles. Even though AIC, BIC and ABIC model estimates indicate superior model fit with four profiles, LMR's p-values point to three profiles being optimum. Despite LMR p-value indicated a three-profile model as the optimum cut-off, further examination of the three-versus four-profile model revealed distinctive substantive differences in favour of the four-profiles model (Fig. 2, Supplementary Figure 9). This was further supported by a high level of profile distinctness (Entropy) and relatively better model fit statistics (Table 2). Based on the high entropy, lower BIC, and ABIC, and substantive difference in patterns in four-profile model, we therefore, settled on using four SRL profiles for subsequent analyses. In comparison to previous studies which have used this survey instrument, a four-profile solution is not unusual, with an entropy of 0.94 being higher than that from findings of those previous studies (Barnard-Brak, Paton, & Lan, 2010). We did not consider models with more than four profiles because we judged the sample as being not large enough to support more profiles (Nylund et al., 2007), coupled with the findings from previous studies that four-profile using OSRLQ tool is not uncommon (Barnard-Brak et al., 2010). Additionally, from our LPA model, the more the number of profiles, the weaker its support for adoption as indicated by LMR test p-value. Results from LPA analysis are illustrated by Fig. 2.

From the four-profile LPA model, Fig. 2 illustrates the estimated sub-scale means of the SRL items grouped by SRL Skill components (i.e. sub-scales). The four identified profiles could be characterised as *Low SRL* (N = 28, 10.61%), *Average SRL* (N = 61, 23.11%), *Above average SRL with low help-seeking* (N = 108, 40.91%), and *High SRL* (N = 67, 25.38%) profiles.

We considered whether there were significant differences in the means of SRL strategies based on profile group membership using the post-hoc Whitney-Mann-Wilcoxon pairwise tests. These tests revealed significant differences in all the multiple comparisons of all the SRL strategies between the four SRL profiles except for Task Strategy between the "Average" and "Above-Average" SRL profiles (p-value = 0.878). SRL strategies for Help-Seeking between the "Low" and "Above-Average" SRL profile were significant (p-value = 0.049). Non-parametric procedure was used because of the violation of the assumption of normal distribution of all the SRL instrument items (Supplementary Table 1). Based on Kruskal-Wallis test statistic, there is a significant difference in the SRL strategies of healthcare providers in low-income contexts by the four-profile membership. This is despite not using the three SRL profile as indicted by the LMR p-value cut-off threshold (Table 2). This, together with the pairwise non-parametric post-hoc tests, suggests overall significant differences across all profiles in almost all SRL subscales. These results are illustrated in Table 3.

Responses to help seeking sub-scale were all low in all groups apart from high SRL profile, with task strategy also having poor performance. These two SRL sub-scales had very high variance as indicated by their standard deviation (Table 3). This might be indicative that interventions to improve persistence and effort-regulation of healthcare providers in LICs when using digital learning platforms might maximise their learning outcomes.

Table 2
Latent profile analysis results for Self-Regulated Learning.

Number of Profiles	Log Likelihood	Parameters	AIC	BIC	ABIC	LMR p-value	Entropy
2	−8509.11	62	17142.22	17363.93	17167.36	0.004	0.990
3	−8257.47	84	16682.94	16983.32	16716.99	0.013	0.957
4	−8122.58	103	16451.16	16819.48	16492.92	0.149	0.940
5	−8045.83	128	16347.67	16805.39	16399.56	0.493	0.960

Note: AIC – Akaike Information Criterion, BIC – Bayesian Information Criterion, ABIC - Sample Adjusted Bayesian Information Criterion, LMR – Lo-Mendell-Rubin test.

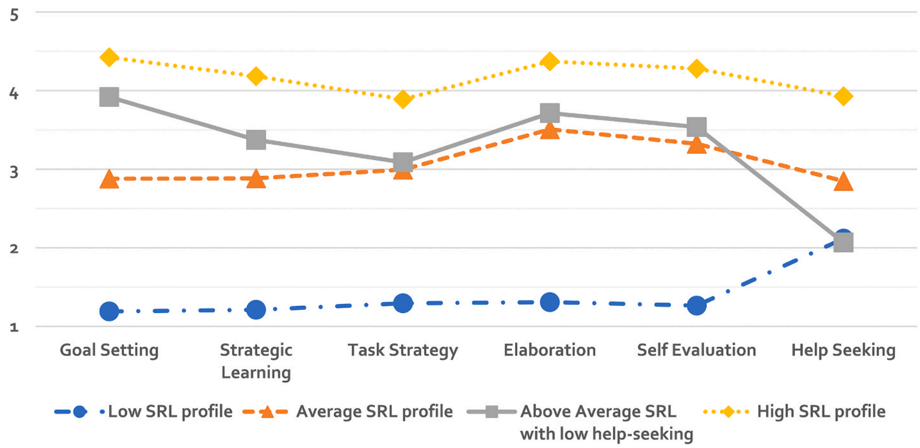

Fig. 2. Self-Regulated Learning profiles of healthcare providers in LICs based expected item means from SRL-TQ tool.

Table 3
Breakdown of participants characteristics by SRL profiles.

Indicator	SRL Profile				
	Low SRL profile	Average SRL profile	Above Average SRL profile	High SRL profile	All
	N (%)	*N (%)*	*N (%)*	*N (%)*	*N (%)*
Counts of health providers in profile	28 (10.61%)	61 (23.11%)	108 (40.91%)	67 (25.38%)	264 (100%)
Clinical Cadre					
Consultant	12 (4.55%)	12 (4.55%)	6 (2.27%)	6 (2.27%)	36 (13.64%)
Medical Officer	15 (5.68%)	25 (9.47%)	42 (15.91%)	18 (6.82%)	100 (37.88%)
Clinical Officer	1 (0.38%)	6 (2.27%)	11 (4.17%)	13 (4.92%)	31 (11.74%)
Nurse	0 (0%)	9 (3.41%)	39 (14.77%)	24 (9.09%)	72 (27.27%)
Other	0 (0%)	9 (3.41%)	10 (3.79%)	6 (2.27%)	25 (9.47%)
Clinical Level					
Active Practice (Not training)	16 (6.06%)	38 (14.39%)	68 (25.76%)	40 (15.15%)	162 (61.36%)
Active Practice (Training)	9 (3.41%)	9 (3.41%)	9 (3.41%)	9 (3.41%)	36 (13.64%)
Student	2 (0.76%)	10 (3.79%)	29 (10.98%)	15 (5.68%)	56 (21.21%)
Other	1 (0.38%)	4 (1.52%)	2 (0.76%)	3 (1.14%)	10 (3.79%)
Age (in years)					
18–24	1 (0.38%)	9 (3.41%)	21 (7.95%)	13 (4.92%)	44 (16.67%)
25–34	11 (4.17%)	30 (11.36%)	54 (20.45%)	29 (10.98%)	124 (46.97%)
35–44	13 (4.92%)	17 (6.44%)	21 (7.95%)	15 (5.68%)	66 (25%)
45–54	2 (0.76%)	4 (1.52%)	9 (3.41%)	7 (2.65%)	22 (8.33%)
55+	1 (0.38%)	1 (0.38%)	3 (1.14%)	3 (1.14%)	8 (3.03%)
Platform					
LIFE	6 (2.27%)	26 (9.85%)	97 (36.74%)	55 (20.83%)	184 (69.7%)
Daktari-Online	22 (8.33%)	35 (13.26%)	11 (4.17%)	12 (4.55%)	80 (30.3%)
	Mean (SD)	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
Experience (in years)	9.61 (7.91)	7.70 (8.25)	7.36 (8.26)	9.21 (9.38)	8.15 (8.52)

3.2. Analysis of SRL latent profiles by respondent characteristics

In general, it is encouraging that for the healthcare providers in this sample, it is only a minority (10.6%) that demonstrated low self-regulation when it comes to learning using digital devices. In this section we report our evaluation of how the identified latent SRL behaviours varied by individual learner characteristics on digital learning platforms. Further descriptive analysis broken down by the identified latent profiles is provided in Table 4.

Healthcare providers in the Low SRL profile using Daktari-Online were on average, less likely to have set goals, had low strategic learning, elaboration and self-evaluation SRL strategies, and were more likely to seek help when they embarked on learning compared to those in the same profile using LIFE (Fig. 3). In general, healthcare providers using Daktari-Online were, on average, more likely to be in the *Low* and *Average* SRL profiles. Those using LIFE were, on average, more likely to be in the *Above Average* and *High* SRL profiles (Table 4).

Due to a lot of demographic sub-categories having no healthcare providers (Table 1, Table 4, Supplementary Table 2) coupled with a relatively small sample, it was inadvisable to conduct a multinomial regression. The multinomial model results would most likely be highly biased due to the danger of model overfitting given the relatively few observations per parameters to be estimated (de Jong et al., 2019). A workaround that was used was multiple logistic regressions with binary outcome of either being in the specific LPA

Table 4
Logistic regression results predicting profile membership.

Profiles	Low (N = 28)			Average (N = 61)			Above Average with low help seeking (N = 108)			High (N = 67)		
Predictors	OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-value
(Intercept)	0.06	0.02–0.21	<0.001	0.07	0.03–0.19	<0.001	2.24	1.17–4.30	0.015	0.27	0.13–0.54	<0.001
Clinical Cadre, Ref: Medical Officer												
Consultant	3.2	1.08–9.53	0.036	1.26	0.47–3.42	0.644	0.3	0.10–0.91	0.033	0.94	0.31–2.84	0.912
Clinical Officer	0.28	0.03–2.41	0.248	2.18	0.65–7.26	0.206	0.35	0.14–0.91	0.032	2.53	0.98–6.52	*0.055*
Nurse	0*	0.00 – Inf*	0.989	1.92	0.62–5.92	0.258	0.56	0.26–1.18	0.128	1.64	0.72–3.72	0.236
Other	0*	0.00 – Inf*	0.993	4.93	1.46–16.68	0.01	0.37	0.13–1.04	0.059	1.38	0.45–4.25	0.57
Level, Ref: Active Practice (Not training)												
Active Practice (Training)	2.25	0.76–6.66	0.142	0.49	0.19–1.29	0.149	0.75	0.28–1.97	0.557	1.78	0.67–4.71	0.249
Student	1.12	0.17–7.24	0.901	1.15	0.45–2.91	0.774	0.8	0.39–1.63	0.544	1.27	0.58–2.77	0.544
Other	1.37	0.13–14.97	0.796	1.26	0.29–5.42	0.756	0.48	0.09–2.69	0.406	1.76	0.37–8.51	0.479
Experience	0.84	0.52–1.35	0.47	0.64	0.43–0.96	0.031	1.1	0.79–1.52	0.581	1.43	1.04–1.96	0.026
Platform, Ref: LIFE												
Daktari-Online	3.34	1.00–11.18	*0.051*	13.06	4.50–37.91	<0.001	0.11	0.05–0.27	<0.001	0.41	0.16–1.07	0.068
Nagelkerke's R^2	0.349			0.225			0.230			0.095		

Note: *Numbers too few to compute reliable estimates.

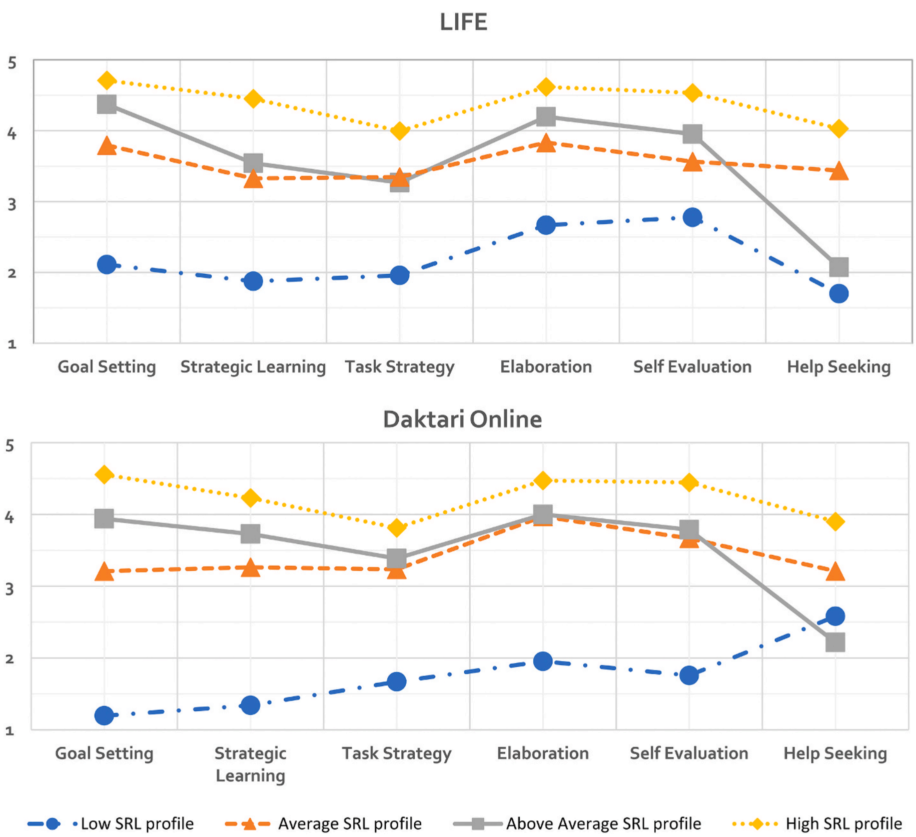

Fig. 3. SRL strategies by digital learning platform.

profile or not. When the odds of profile membership are broken by background characteristics, high self-regulated learners significantly differed from the other profiles on the basis of experience. In this profile, with each increase in a year of experience, health providers had 43% increase in the odds of being in high SRL profile (Table 5). Counter-intuitively, consultants -who are the highest skilled healthcare providers-had three times the odds of being in low SRL profile compared to other clinical speciality levels. Computer-based online learning platforms such as *Daktari-Online* was significantly associated with the odds of being in the average or above-average SRL profile. Healthcare providers in the using computer-based learning platforms were 13 times more likely to be in the average SRL profile compared to those using the smartphone learning platform. They also had a 36% decrease in the odds of being in the average SRL profile with a unit increase in their years of experience (Table 5). Healthcare providers in the above-average SRL profile with low help-seeking were 89% less likely to be users of the Daktari-Online platform. They were also 70% and 65% less likely to be consultants and clinical officers (Table 5). Due to the low numbers in the low self-regulated learning profile, some estimates in that column are considered highly unreliable and findings for this profile should be interpreted cautiously.

3.3. Influence of the latent SRL profiles on healthcare providers learning gains

For the second research question, we evaluated the influence the identified latent SRL profiles had on healthcare providers'

Table 5
Self-regulated learning skills by profiles.

SRL Skill	Low SRL profile	Average SRL profile	Above Average SRL with low help-seeking	High SRL Profile	Kruskal -Wallis Test*
	Mean (SD)	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*p-value*
Goal Setting	1.29 (0.67)	3.09 (1.07)	4.00 (1.02)	4.51 (0.64)	<0.001
Strategic Learning	1.36 (0.77)	3.03 (1.09)	3.45 (1.30)	4.33 (0.91)	<0.001
Task Strategy	1.59 (1.14)	3.03 (1.19)	3.22 (1.42)	3.97 (1.24)	<0.001
Elaboration	1.83 (1.33)	3.43 (1.17)	3.88 (1.15)	4.44 (0.79)	<0.001
Self-Evaluation	1.73 (1.18)	3.22 (1.14)	3.70 (1.16)	4.39 (0.87)	<0.001
Help-Seeking	2.16 (1.42)	3.09 (1.16)	2.24 (1.38)	4.00 (1.20)	<0.001

Note: *Kruskal-Wallis Test performed row-wise i.e. by SRL skill.

learning gains. We used learning performance data in the form of normalised learning gains (Marx & Cummings, 2007) from healthcare providers who used LIFE. The records of healthcare providers performance from Daktari-Online are neither in the form capable of generating learning gain scores nor covered by ethical approvals. They were therefore not requested. The calculation of learning gains used here whose scale lies between −1 and 1, is explained in much more detail in the Supplementary material (Multimedia Component 1) and has also been covered in detail in published literature (Marx & Cummings, 2007).

When the normalised learning gain is positive, the healthcare providers were making performance gains in what they learnt when it is evaluated as a ratio of the amount they could have learned. From learning gain analysis of LIFE data, learners in the *above-average* and *high* SRL profiles had substantively more repeated plays with improved performance than healthcare providers in the other SRL profiles (Fig. 4). With each repeated learning session, feedback on individual learning task was adapted for learners who were struggling to make gains Tuti et al. (2020). All included SRL profiles had positive learning gains with each repeated learning cycle, but healthcare providers in low SRL profiles -who were more likely to be consultants (Table 5)- had the least number of repeated learning sessions, but achieved maximum learning gains by their third learning session. Consisted with low task strategy SRL skill, learning persistence of the healthcare providers in all profiles apart from *low* SRL was not associated with maximised learning gains. The average SRL profile learners ceased learning when their performance stagnated or deteriorated (Fig. 4). Due to the low numbers in the low SRL profile, findings for this profile from Fig. 4 should be interpreted cautiously.

4. Discussion

4.1. Summary of findings

The current study was intended to generate insights about Self-Regulated Learning (SRL) by healthcare providers in low-income countries on digital learning environments, whether they be computer- or smartphone-based. In summary, for our first research question, using Latent Profile Analysis (LPA) we demonstrated that there are four SRL profiles in this cohort of learners: *high*, *above-average with low help-seeking*, *average*, and *low* SRL profiles. Healthcare providers in the *high* SRL profile scored relatively highly in each SRL sub-scale (strategy) with the opposite being true for those in *low* SRL profile. Healthcare providers in average SRL profile had average and relatively monotonic response to all SRL sub-scales while those in the above-average SRL profile having low response to help-seeking behaviours and above-average to high response in the other SRL sub-scales.

Consultants had three times the odds of being in the low SRL group, and online computer-based learners had 13 times the odds of being the average SRL profile. The above-average with low help-seeking SRL learners were 89% less likely to have used Daktari-Online and at least 65% less likely to be clinical officers or consultants. Unit increase in the years of experience in providing healthcare significantly increased the odds of healthcare providers being in the high SRL profile by 1.5 times (Table 5). Only 10.1% of healthcare providers who took part in the study could be regarded as having low self-regulated learning. In addressing our second research

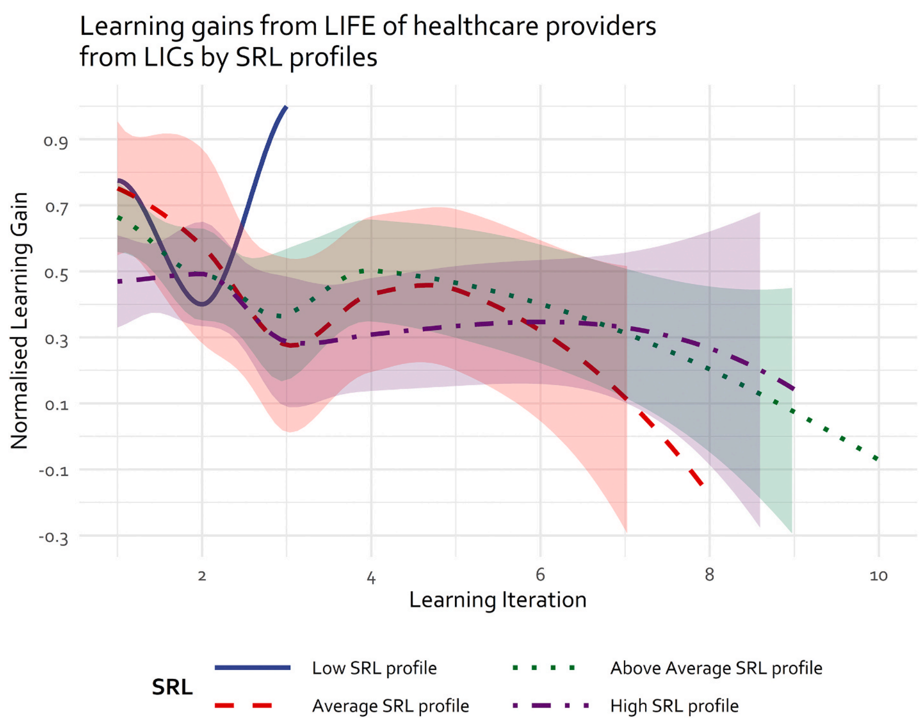

Fig. 4. LOESS plot of the healthcare providers learning gains by SRL profiles.

question, when knowledge gain was considered for learners where that information was available (i.e. LIFE users), compared to healthcare providers in the low SRL profile (who were mostly consultants), the other three SRL profiles had lower normalised gains which were never maximised even with more repeated learning cycles. This might be because the LIFE learning content is typically not easily and affordably accessible to lower clinical cadres; they are likely to have had limited previous training exposure to it. Even within self-directed learning, it might require more instructional support to ensure maximum learning gains are realised as illustrated in Fig. 4. Given the varied but low task strategies and help-seeking behaviours in the SRL profiles (Table 5), it is conceivable that the lack of maximising on the possible learning gains from using the LIFE platform in all SRL profiles apart from low SRL profile can be attributable to a low persistence and effort-regulation with limited help provided/sought. The low SRL profile which had higher odds of having consultants than any other cadre (Table 5), and demonstrated maximisation of learning gains with minimal reinforcing of the learning content and earliest drop-out (Fig. 4), might be indicative that the content might not be as challenging for learners in this profile. Given that the LIFE learning data was from emergency care-giving scenarios, a perfect performance was the target; Less than perfect scores could indicate a knowledge gap that needed to be addressed to reduce risk of patient mortality in the care-giving scenario or possibly, a ceiling effect of the learning content. Additional qualitative work is being conducted to understand how the context of clinical practice and learning platform use inform healthcare providers' perception of their own SRL. The qualitative work will help explore in greater depth the differentiating SRL characteristics of the healthcare providers' that reflect their context of learning.

4.2. Comparison to other studies

Unlike previous studies that have examined LPA for adult learners on digital devices, we found that for healthcare providers in LICs, four substantive latent SRL profiles may exist as opposed to three (Abar & Loken, 2010; Vanslambrouck et al., 2019). Compared to previous studies, the extra "new" profile (above-average SRL profile with low-help seeking) had a majority of healthcare providers unlike the other studies which had a majority of the learners falling in the average SRL profile (Abar & Loken, 2010; Vanslambrouck et al., 2019). Our study also sought to ensure that a diverse population of healthcare providers from LICs not limited by clinical speciality, cadre, or digital learning platform were included in the analysis. This makes our study substantively dissimilar to other empirical studies looking at SRL in clinical training (Cho et al., 2017; Keçeci, 2017). In line with the most recent review of SRL in clinical settings, evidence suggests that further research is needed to unravel and reconceptualise the sub-processes of SRL that are relevant to the clinical context to contribute to more elaborate context-specific SRL frameworks (van Houten-Schat et al., 2018). We believe that our study serves as a response to that call, is especially relevant to low-income countries and makes a good starting point for future implementation of context relevant SRL informed digital learning interventions for healthcare providers in this region.

4.3. Study limitations

While LPA model had reasonably good performance on the survey data unlike the planned confirmatory factor analysis, the relatively low explained variance in the models, linked to the small sample, is disconcerting (Table 5). This is most likely because of the number of healthcare providers analysed, making it hard to give more precise estimations. Nevertheless, the study was looking at a largely unexplored topic and population (i.e. latent quantitative analysis of SRL in low-income contexts such as a Sub-Saharan Africa). The findings have helped provide nuanced understanding of SRL especially for digital learning interventions used in clinical training where there is promise of much positive gains in patient outcomes in this region. We argue that our findings, internalised as a case-study underpinned by Self-Regulated Learning theory, follow the analytical and transferability model of generalisability (to context) as opposed to statistical generalisability (Polit & Beck, 2010). This type of generalisability can –and will be-enhanced by use of an in-depth qualitative study, which is currently being done to aid better understanding and explanation of our findings.

The recruitment efforts were focused on reducing selection bias, with the final survey sample based on voluntary self-selected participants. Therefore, we cannot rule out that our findings might be affected by voluntary response bias. While the sample of healthcare providers used in this study is not statistically generalisable to the population of all healthcare providers in low income contexts, its make-up (from those in training to specialists, at all healthcare provision categories) provides a highly informative and situated source of understanding self-regulated learning of healthcare providers in resource-constrained settings for clinical training on digital platforms, a gap recognised by most recent systematic reviews in these areas (Car et al., 2019; Gentry et al., 2019). We are yet to find any comparable studies on this subject in this context for this domain. While SRL approaches of professionals and students might be different, the boundary between professional practice and student practice in LICs is usually blurry due to how students are deployed within the health system to mitigate against the health workforce shortage (WHO, 2016). Findings and implications should be cautiously interpreted based on the context of the health system and healthcare practice.

4.4. Implications of findings

Our findings should be interpreted cautiously for several reasons including the known disparities between the learning platforms, the pragmatic constraints on recruitment methods, and the lack of available information to better differentiate between the respondents' context of learning. Nevertheless, the findings raise important issues for the role of technology in healthcare training in low-income countries.

Learners in the low SRL profile are more likely to be of higher clinical cadre (Table 5). They demonstrate earliest drop-out during learning just after they achieve maximum learning gain (Fig. 4). Apart from the possible explanation that the content might not be as challenging for learners in this profile, another possible explanation for the low SRL behaviour of these learners might be that their learning context -if conceptualised as a set of situational stimuli-needs more restructuring to improve both their learning experience and regulation (de la Fuente-Arias, 2017). This might be because the clinical practice context which informs their learning is likely a-regulatory i.e. it does not promote self-regulation in learning but instead needs more external regulation (de la Fuente-Arias, 2017). To what extent this is true in LIC context remains unclear and is being investigated qualitatively. For regulated learning to be more effective for the low SRL learners, it might need to be restructured in a way that caters for the role of the interaction between personal learner and contextual characteristics. In exploring the plausibility of these a-regulatory learning behaviours, future research needs to investigate what healthcare providers' expectations of success in SRL are and how they value SRL in view of their contextual contingencies. This will generate better understanding of their learning experiences that can inform the implementation of learning platforms that better engage and challenge them as they continue making gains in their learning. Additionally SRL measurement tools might be incongruent to a healthcare provider's learning efficiency (Rovers et al., 2019), which is necessary to address in future developments in education (de Bruin & van Merriënboer, 2017). Efficiency in learning, which might be another reason of the differences observed in learning gains between the SRL groups (Fig. 4), might be better addressed using other learning theories e.g. the Cognitive Load Theory (Phan, Ngu, & Yeung, 2017). Future research can seek to evaluate how to combine the alternative learning theories linking efficiency in learning and focus on learner's attempts to deal with complex information efficiently with SRL theory, which focuses on learner's effort to monitor and control their learning (de Bruin & van Merriënboer, 2017).

From findings of RQ2, the implication here is that scaffolding of content and instructional support might possibly play a significant role in ensuring continuous professional development of healthcare providers in low-income contexts, by ensuring that their motivation to engage in constant learning is targeted by their SRL profile characteristics (Duffy & Azevedo, 2015). Given the varied but low task strategies and help-seeking behaviours in the SRL profiles (Table 5), it is conceivable that the lack of maximising on the possible learning gains from using the LIFE platform in all SRL profiles apart from low SRL profile can be attributable to a low persistence and effort-regulation with limited help provided/sought. In low SRL profile, given that it is has higher odds of having consultants than any other cadre (Table 5), and demonstrated maximisation of learning gains with minimal reinforcing of the learning content and earliest drop-out (Fig. 4), this might be indicative that the content might not be as challenging for learners in this profile.

SRL strategies might well have varied by platform given the differences between LIFE and Daktari-Online platform, with the former being free, mobile-based, interactive and gamified, using formative assessments, while the latter requiring paid subscription, and being computer-based, non-gamified and passive, using summative assessments (Table 5, Appendix A) Supplementary material (Multimedia Component 1). For example, compared to Daktari-Online, the LIFE smartphone app narrowed the gap between Low- and High- SRL profiles specifically for elaboration and self-evaluation strategies, through exploring novel adaptive learning approaches to scaffolded feedback, which are reported in detail in a related study Tuti et al. (2020). Alternatively, based on knowledge gaps that learners are keen to address and their SRL profiles and platform of choice, learners could be given access to a wider range of learning scenarios and allowed to also structure and customise the learning content they receive to reflect clinical scenarios they struggle with. This can be explicitly targeted during the scaling up of the Low-Dose-High-Frequency (LDHF) learning approach commonly used (and considered effective) in face-to-face clinical training in LICs (Atukunda & Conecker, 2017) using digital learning platforms. Such evaluations of platform features' effect on SRL strategies and outcomes require further systematic investigation given their substantive nature. Platforms similar to LIFE that use LDHF training approach might help maximise learning gains if combined with cascaded content challenge and instruction support levels to encourage a more engaging learning experience. Additionally, it could serve as a means for facilitating the refreshing and updating of healthcare providers' knowledge in keeping up with the ever-evolving clinical practice guidelines.

Given that task strategy and help-seeking had low item means across the profiles, this might imply that healthcare providers generally have low effort-regulation when it comes to learning on digital devices in this context. Additionally, help-seeking -while being lowly regarded in clinical context due to being misconstrued as evidence of incompetence-might not be an easily improvable SRL strategy even though its most likely to positively influence persistence and effort regulation (Dueñas et al., 2018; Maibach, Schieber, & Carroll, 1996).

Learning also takes place in a social practice, and therefore tutors and colleagues are vital for any healthcare provider's self-regulated learning in their context of practice. However, in this study, the focus was on how individual healthcare providers perceived themselves to have overt control over their self-regulated learning on digital platforms as opposed to how others in the clinical context of practice influence them (Berkhout, Helmich, Teunissen, van der Vleuten, & Jaarsma, 2017). Future research should address if and how the nature of learning in social and collaborative contexts might influence SRL behaviours (e.g. Help-seeking) of healthcare providers' in LICs. This might explain, for example how external learning regulation from using clinical peer influence for learning support (Saqe-Rockoff, Ciardiello, & Schubert, 2019; van Schaik, Plant, Diane, Tsang, & O'Sullivan, 2011) after catering for individual learning motivation (Duffy & Azevedo, 2015) on their preferred digital learning platform. It might also help address the a-regulatory learning behaviours of healthcare providers that we have previously alluded to and highlight the social practices for online learning in LICs context.

5. Conclusion

Self-regulated learning is critical for encouraging voluntary upskilling of healthcare providers in LICs, especially when using digital learning interventions. Although insight into healthcare providers' SRL in digital environments is vital for enabling personalised instructional support necessary for better patient outcomes, research from low-income contexts is lacking. This study adds to empirical evidence on the SRL of clinicians in these contexts by generating insights into how these healthcare providers self-direct their learning on digital platforms. In addressing the first research question, the results of this study suggest the differences in SRL between healthcare providers from these contexts who use digital learning environments, as they indicate four SRL profiles: *Low*, *Average*, *Above Average with Low Help Seeking* and *High* SRL profile. From these profiles, healthcare providers in the high SRL profile were likely to be junior doctors and nurses, had relatively high endorsement of Goal Setting, Strategic Learning, Task Strategy, Elaboration, Self-Evaluation, and Help-Seeking SRL strategies with the converse being true for those in Low SRL profile who were more likely to be consultants. Healthcare providers in average SRL profile had average and relatively monotonic response to all these strategies while those in the above-average SRL profile demonstrated low affinity for help-seeking behaviours while having above-average to high response on all other SRL strategies. Longer experience in providing healthcare significantly increased the odds of healthcare providers being in the high SRL profile. Healthcare providers in the average SRL profiles were more likely to be users of computer-based digital learning compared to smartphone-based learning. From the second research question, from exploring the SRL profiles' association to healthcare providers' learning gains, the two average and the high SRL profiles had lower normalised learning gains but more reinforcement learning cycles compared to healthcare providers in the low SRL profile, even though it is only learners in the low SRL profile that were able to attain maximum learning gains. The implications of our findings are that healthcare providers from these LICs contexts who are using digital learning environments are typically, at least moderately self-regulating their learning, but that wider access to (modifiable) learning content scenarios, or scaffolding instructional design might play a bigger role in enhancing task strategy and persistence in the SRL of healthcare providers from LICs when their motivation to engage in continuous but challenging learning, is targeted.

Future research into SRL on digital platforms for clinical training utilising scenario-based modular content (e.g. for low-dose-high-frequency model that is commonly found in LICs resource settings) might explore how to better enhance content complexity or/and instructional support scaffolding. This could be important in enhancing maximised learning over spaced repetition of learning when informed by -for example-healthcare providers' SRL task and help-seeking strategies in effort regulation.

CRediT

Timothy Tuti: Conceptualisation, Methodology, Software, Data curation, Visualization, Investigation, Writing – original draft, Writing- Reviewing and Editing; Chris Paton: Supervision, Funding acquisition, Project administration, Writing- Reviewing and Editing; Niall Winters: Investigation, Supervision, Writing- Reviewing and Editing.

Ethics approval and consent to participate

The analyses described in this study have been approved by the KEMRI's Scientific and Ethical Review Committee (#3444) and the Central University Research and Ethics Committee of Oxford University (#ED-CIA-18-106). Individual healthcare provider consent was elicited from the web tool and within the smartphone application before collection of any demographic data.

Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2021.104136.

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