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Online learners' self-regulated learning skills regarding LMS interactions: a profiling study

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Abstract
This profiling study deals with the self-regulated learning skills of online learners based on their interaction behaviors on the learning management system. The learners were profiled through their interaction behaviors via cluster analysis. Following a correlational model with the interaction data of learners, the post-test questionnaire data were used to determine self-regulated learning skills scores during the learning process. Regarding the scores, the clusters were named through the prominent interactions of the learners yielding three clusters; actively engaged (Cluster1), assessment-oriented (Cluster2), and passively-oriented (Cluster3), respectively. The profiles in the clusters indicate that assessments were mostly used by the learners in Cluster2, while the frequency of the content tools was high in Cluster1. Surprisingly, some tools such as glossary, survey, and chat did not play a prominent role in discriminating the clusters. Suggestions for future implementations of self-regulated learning and effective online learning in learning management systems are also included.

Keywords Learning analytics · Online interactions · Self-regulated learning · Learning management systems

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Introduction

Learners need to have more self-regulated learning (SRL) skills to be successful in online learning. However, understanding the actions, strategies, and goals of SRL is a more challenging task. Since learners have different abilities and knowledge, they employ different strategies through their SRL skills in online learning settings. Thus, increasing attention has been shown to online SRL over the last few years (Broadbent, 2017; Broadbent & Poon, 2015; Eggers et al., 2021). In the field of learning analytics (LA), recent techniques in LMSs provide possibilities to understand self-regulation in online learning. Using LA techniques, researchers are still studying how to reveal or measure SRL in online settings. The studies are ongoing answering the questions of what to trace, how to collect data, and what kind of techniques are useful for revealing SRL (Viberg et al., 2020). For example, some LA studies analyze online interaction behaviors and create indicators of SRL phases from learners' trace data (Kia et al., 2021).

In recent years, attention has been focused on grouping learners having similar interaction behaviors in LMSs. These studies are limited in number and use interaction data (Sun et al., 2023) to analyze some variables among these groups (eg. learning performance). Although some of the research reported some information about the groups' SRL behaviors, studies explaining these behaviors covering interactions with LMS tools are still nascent. Thus, this study highlights the importance of the use of LMS tools and associating the tools with groups' SRL behaviors. The present study grouped learners' regarding Zimmerman's (2000) three-phase model and captured their interaction behaviors with LMS tools.

Theoretical background

Many studies have captured online SRL behaviors (Ye & Pennisi, 2022) and perceived online SRL strategies (Sun et al., 2018) by applying appropriate SRL models. Some SRL models focus on specific dimensions such as emotions and motivation (Boekaerts, 2011), on cognition (Winne & Hadwin, 1998) and some others focus on specific contexts such as collaborative learning (Jarvela & Hadwin, 2013). In addition, Pintrich's (2000) model focuses on the role of cognition and metacognition processes and learning behaviors through resource management. Despite the different conceptualizations in the models, the SRL is generally considered a temporal dynamic process that covers planning and forethought, performance and monitoring, and reflection and evaluation phases (Alonso-Mencía et al., 2020; Saint et al., 2020; Zimmerman, 2000).

As one of the most cited SRL models, Zimmerman's model (2000) described the SRL in three cyclical phases including forethought, performance, and self-reflection (Broadbent et al., 2020). In the forethought phase, learners analyze the task and set goals and plans accordingly. This phase is strengthened by several variables such as motivation, self-directed learning, and self-efficacy. It is useful to elaborate on this point by considering the relevant variables. Self-directed learning and self-efficacy play important roles in the energizing forethought phase of SRL. Self-directed learning refers to the process in which learners take responsibility for their learning and actively monitor their academic progress (Knowles, 1975). The motivation toward an activity is also a contributing factor to self-directed change (Usher & Schunk, 2017). It entails translating psychological capacities into task-related skills and is crucial for adeptly adapting to academic activities. On the other hand, self-efficacy is an individual's assessment of their capabilities to complete a specific task (Bandura, 1997). It impacts students' choices, efforts, perseverance, and achievements. Students with high self-efficacy who participate in self-directed learning are more likely to regulate their learning effectively (Bandura, 1997; Parveen et al., 2023). Self-efficacy helps students to actively engage in the learning process, while self-directed learning empowers them to take control of their learning and apply effective strategies. Then, the performance phase takes place in which learners manage their learning process by working on the task using several self-control and self-observation strategies to monitor their progress. In the self-reflection phase, learners evaluate their work and react to the result (Broadbent et al., 2020). The SRL models guide educators to design learning environments for activating learners to display self-regulated behaviors to achieve their learning goals (Bannert et al., 2014). In the current study, SRL strategies were derived from Zimmerman's SRL model (2000) as presented in Fig. 1.

During the last three decades, a wide variety of self-reporting tools have been used to determine learners' SRL. Roth et al. (2016) in a systematic literature review reported the following instrument types: questionnaires, interviews, think-aloud

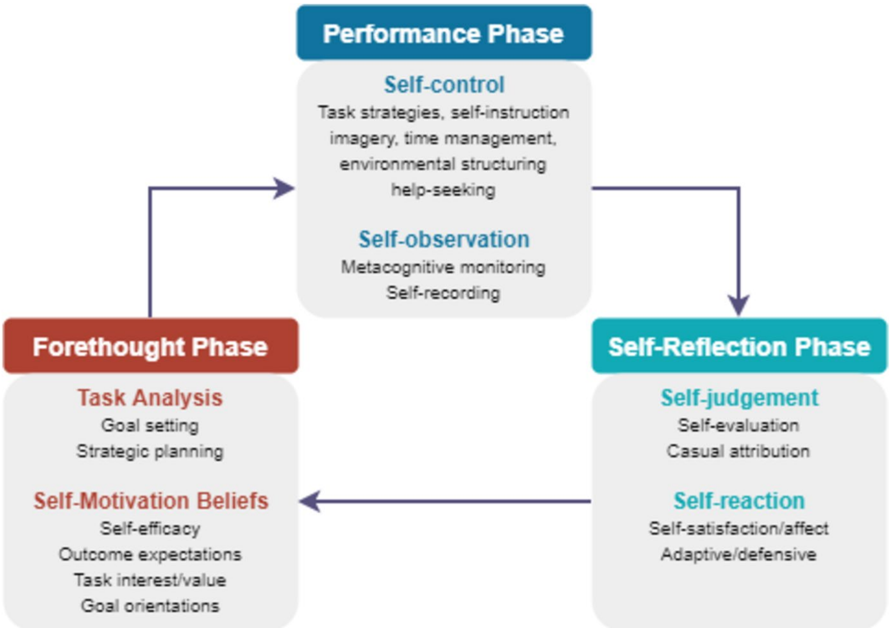

Fig. 1 Zimmerman's cyclic SRL model

protocols, and learning diaries. However, researchers have some criticisms of some of these self-reported tools in online contexts. For instance, Duncan and McKeachie (2005) pointed out that the Motivated Strategies for Learning Questionnaire covers a range of scales from the performance phase but does not measure self-regulation in the preparatory and appraisal phases (Li et al., 2020). The Metacognitive Awareness Inventory does not include time and environment management. In addition, these instruments are generally appropriate for the SRL deployment in traditional face-to-face education (Cho & Summers, 2012). Furthermore, "the self-regulated online learning questionnaire" is accepted as being specifically designed for use in online learning (Jansen et al., 2017). Accordingly, to profile learners regarding their SRL, we used this questionnaire to provide learners with steady SRL measures.

Learning analytics for understanding online self-regulated learning

Understanding SRL in online learning is vital for better online instruction. However, it is difficult to reveal the deployment of SRL strategies (Efklides, 2011; Winne & Perry, 2000; Liz-Dominguez, 2022) because of their dynamic and temporal nature in the online learning process. An emerging literature has used online learners' interaction behaviors to understand in online learning platforms (Kokoç et al., 2021) and LMSs (e.g., Baker et al., 2020; Cicchinelli et al., 2018; Jansen et al., 2020; Li et al., 2020).

The data stored in LMS covers the logs of interaction behaviors (Lerche & Kiel, 2018). Interaction behaviors are any kind of meaningful interactions about learning such as delivering learning materials (e.g., lecture video, navigation in a web page), engaging in learning activities (e.g., quizzes, assignments, and discussion, forum, chat), and acting in assessment activities (e.g., exams, and surveys) (Lewis et al., 2005). The interaction data are used as indicators of learners' SRL skills (Viberg et al., 2018) and linked to metrics (e.g. clicks) of SRL strategies. For instance, a study focused on interaction behaviors and found that using metacognitive prompts supported learners' SRL in learning activities (Siadaty et al., 2016). Another study included the number of posted forum messages per week and the number of forum views to provide information about the learners' future behaviors in the course (Xing et al., 2016). Similarly, Xing and Du (2019) used online learners' interaction data such as accessing the course, using the grade books, calendar, or other activities.

To understand the relationship between the deployment of SRL strategies; learners' use of tools for the SRL strategies comes to the fore (Carless & Boud, 2018; Carless et al., 2011). In this case, researchers generally, suggest profiling (Lust et al., 2011) which may offer some important insights into relations between SRL skills and interaction behaviors, and contribute to a deeper understanding of the SRL skills of online learners. Some previous studies profile learners first and then identify their SRL. They examine SRL profiles in specific contexts and rely on interaction data instead of learners' self-reported measures of self-regulatory strategies. Learners shift their learning profiles across different domains and even within a course in response to contextual factors. Researchers have proposed that SRL profiles are dynamic per se (Jang et al., 2017; Shell & Soh, 2013). According to Panadero et al.

(2016), this type of assessment takes SRL as an event (time-based and task-related of known start and end), rather than considering it a steady feature of the learner. Nonetheless, it is also important to consider SRL as a feature of the learner and confirm the indicators of online SRL as an event. Additionally, previous studies also highlighted that the analytical methods to detect SRL need to be tested for the extent and conditions (Kia et al., 2021). Thus, some new profiling studies are needed to understand how learners act in the LMS regarding their SRL profiles. Namely, studies that provide detailed explanations about the types of SRL strategies and learning tools of LMSs that the learners use.

Previous studies showed that learning tools of LMSs were generally used for resource sharing, communication, or information searching in forums, blogs, wikis, or chat platforms (Cicchinelli et al., 2018; Dabbagh & Kitsantas, 2012; Jansen et al., 2020; Maldonado-Mahauad et al., 2018). The resource-sharing tools, search tools, and help tools were also found particularly helpful for self-evaluation, task strategies, and goal setting (Chou et al., 2018; Kitsantas, 2013). There are very few studies examining learning tools and self-regulation together, and these studies do not include profiling. In one of these studies, Selvi and Panneerselvam (2012) used a web-based system that allows learners to monitor their learning process, manage their time, and assess their knowledge through the system using a set of digital tools. They found that there was considerable development in self-regulation skills at the end of the course. Another study found that learners who reported stronger SRL skills were more likely to visit course materials (Kizilcec et al., 2016).

Motivation for the research

Previous studies suggested that a poor understanding of SRL leads to a wasted opportunity for improving students' learning processes (Nilson, 2013). Thus, educators need to benefit more from the tools supporting learners' learning in the LMSs (Araka et al., 2020; Çakıroğlu et al., 2019; Song & Kim, 2020; Viberg et al., 2020). Interventions for enhancing SRL can be successful when the instructional designers or instructors know more about how learners know, use, engage, or adopt LMS learning tools (Li et al., 2020). Applying LA techniques, learners may know what they can do within the LMS learning tools for better learning outcomes (Roll & Winne, 2015). Accordingly, instructors can be informed about the relationship between active learning strategies for deploying SRL skills and the use of LMS learning tools, and students to understand how well online learners regulate several aspects of their learning processes. Understanding the use of LMS tools for promoting SRL strategies may provide hints for instructional designers to use interactions reflecting self-regulatory strategies in their course designs. In sum, still, there are still many difficulties in accessing necessary data or using appropriate analysis methods in the LA studies to better understand SRL in online learning settings. This study fills the gap in understanding the use of the LMS learning tools and their relations with SRL. This study profiled students' SRL skills as they perceived in the self-report data and associated the profiles with their interactions with LMS learning tools and the following research questions are formulated:

- What are clusters constructed through online learners' interaction behaviors on LMS tools?
- Which SRL skills of online learners reflected on their most used LMS learning tools?

Method

The current profiling study was conducted employing clustering analysis to answer the research questions. The clustering method provides powerful algorithms to profile learners into appropriate groups based on their attributes and features available in educational datasets (Liu & Koedinger, 2017).

This study used convenience sampling to select the participants due to the difficulties of conducting a large-scale online course with a wider range of learners. A total of 65 undergraduate students who enrolled in a third-year course participated in the study at the beginning of the study. Five students did not log in to the online learning environment (Moodle LMS) at least once and never participated in any course activities and learning tasks. Those students who dropped out of the course due to unknown reasons were excluded from further analysis. Thus, the study data were collected from 60 out of the 65 enrolled undergraduate students (33 male, 27 female) with the age range from 20 to 24. The average age was 22.03 (SD = 1.43). They had taken at least one online course in university before the study. The data were collected in the first term of the 2019 academic year. The participants answered an online scale about their online self-regulation. All participants agreed to participate in the study voluntarily. They were assured about the anonymity and confidentiality of the study data.

Procedure

The context of the study was a third-year computing course titled Operating Systems and Applications in an Instructional Technology teacher education program at a large-scale public university in Turkey. The study was conducted in a blended 16-week undergraduate course planned to introduce the teacher candidates to basic operation systems concepts. The course aimed to provide basic knowledge, foundation concepts, and principles of operating systems for evolving directions in system architecture. The instructional package included process and thread management, deadlocks, input/output device management, memory management, central process unit, scheduling algorithms, and file management in operating systems. The course was delivered three hours per week through Moodle LMS asynchronously. The learners studied with Scorm packages, short course videos, presentations, and books in PDF format each week. These contents were supported with visuals and audio materials in some weeks. During the course, learners were able to interact with each other and with the instructor using Moodle tools such as forums, glossary, and messaging. They were given weekly assignments and allowed to use tools including forums and chat for discussions about these assignments and to work collaboratively. The instructor who is also one of the researchers guided the learning process and encouraged the learners to follow learning activities. He also presented them with how to search for information for their learning tasks.

Measures

Interaction data indicating online learning behavior

We used learner-generated interaction data derived from Moodle time-stamped logs, the aim of which was to understand the SRL skills extracted from the learners' online learning experiences in Moodle. Data reflecting the online learning experiences of learners in the online learning process were extracted from the Moodle database by using MySQL queries. The interaction data consists of learners' interactions with Moodle components such as forum, assignment, content, chat, glossary, assessment, and survey tools. Raw data were pre-processed and named in a suitable format. Adjusted variables reflecting a list of activities in the learning process in Moodle are presented in Table 1.

As seen in Table 1, seven variables reflecting learners' online interaction behaviors were calculated with the accumulated number of events for each type of activity. Some of the variables were re-organized by the researchers by the nature of the relevant events. For example, the total of assessment-related actions such as quiz attempt, quiz submission, quiz view, and access quiz report was considered as assessment interaction data, as these actions are learners' clicking events in the quiz activity.

Online SRL scale

Considering Zimmerman's SRL model (2000), we used the Online SRL Scale developed by Barnard et al. (2009) and translated to Turkish by Kilis and Yıldırım (2018) for measuring perceived SRL skills at the end of the study. The scale includes six subscales and 24 items in the form of a five-point Likert type ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Regarding reliability, internal consistency values were measured via Cronbach alpha 0.95 for the whole instrument and ranged between 0.67 and 0.87 for its six sub-factors. All the factors have Cronbach alpha values higher than 0.70 except one which is very close to 0.70 and therefore, all the sub-factors yielded acceptable values (Hair et al., 2010) regarding internal consistency and found acceptable. According to the findings, with a χ^2/df ratio value of 2.45, the translated instrument was acceptable. The worth of fit values was found to be $\chi^2/df = 2.45$, RMSEA = 0.06, RMR = 0.08, SRMR = 0.06, TLI = 0.89, CFI = 0.90, GFI = 0.86, AGFI = 0.84 and NFI = 0.80. According to these values, it can be said that GFI, AGFI, CFI, TLI and NFI observable fit values were slightly lower than acceptable value, but very close to good fit values while RMSEA, SRMR, and RMR fit values indicated an acceptable and good fit. The scale items and description of the factors are presented in Table 2. All of the learners completed the scale and it took approximately 20 min on average.

Table 1 List of variables reflecting online interaction, related activities, and their meaning

Variables	Activity	Meaning
Assessment interaction	Quiz activities enable teachers to create and conduct online quizzes and give feedback to students	The events related to any interactions with quiz activities and quiz reports
Forum interaction	Forum activities allow students to have asynchronous discussions	The events related to any interaction with forum pages and discussion messages
Content interaction	Content tools enable SCORM packages, books, and learning materials to be included as course content	The events related to viewing various kinds of learning materials in the course
Assignment interaction	Assignment activities allow students to upload their files on learning tasks and enable teachers to evaluate them	The events related to viewing various sections of assignments including submission, feedback, and reporting pages
Chat interaction	Chat activities enable students to have a real-time discussion	The events related to any interaction with the chat tool
Survey interaction	The survey tool allows teachers to gather feedback from students	The events related to any interaction with survey forms
Glossary interaction	The glossary activity allows students to create a list of definitions of course content	The events related to creating a new glossary entry

Table 2 Online SRL factors, their meaning, and items

Factors	Meaning	Items
Goal setting	Goal setting involves selecting personal learning standards for short and long-term learning goals	I set standards for my assignments in online courses
		I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester)
		I keep a high standard for my learning in my online courses
		I set goals to help me manage study time for my online courses
		I don't compromise the quality of my work because it is online
Environment structuring	Environment structuring looks at how the physical environments may be rearranged to avoid distractions and enhance learning (Yen et al., 2016)	I chose the location where I study to avoid too much distraction
		I find a comfortable place to study
		I know where I can study most efficiently for online courses
		I chose a time with few distractions for studying for my online courses
Task strategies	Task strategies include behaviors to curtail the distractions to learning such as taking notes, reading aloud, preparing questions, and pursuing extra work	I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom
		I read aloud instructional materials posted online to fight against distractions
		I prepare my questions before joining in discussion forum
		I work on extra problems in my online courses in addition to the assigned ones to master the course content
Time management	Time management consists of allocating, scheduling, and distributing time for learning. It indicates an effective use of time while performing certain goal-directed activities (Claessens et al., 2007)	I allocate extra studying time for my online courses because I know it is time demanding
		I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule
		Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days

Table 2 (continued)

Factors	Meaning	Items
Help-seeking	Help-seeking signifies being aware of a problem, deciding to seek help, and using the scaffolding of help to solve problems in the online learning environment (Chou et al., 2018)	I find someone knowledgeable in course content so that I can consult with him or her when I need help
		I share my problems with my classmates online, so we know what we are struggling with and how to solve our problems
		If needed, I try to meet my classmates face-to-face
		I am persistent in getting help from the instructor through e-mail
Self-evaluation	Self-evaluation means setting standards and using them for self-judgment and comparing self-monitored information with a goal (Zimmerman, 2000)	I summarize my learning in online courses to examine my understanding of what I have learned
		I ask myself a lot of questions about the course material when studying for an online course
		I communicate with my classmates to find out how I am doing in my online classes

Data analysis

The study data were analyzed according to the research questions. To investigate the relationship between SRL skills and the number of interactions with tools, correlation analysis was conducted in the study. Clustering analysis was employed to explore online learner profiles based on their interaction data. One-way analysis of variance (ANOVA) was run to investigate whether there were differences among clusters in terms of SRL sub-skills. Effect sizes were calculated to see the practical significance of ANOVA results. Recommendations of Cohen (1988) were considered to interpret effect sizes.

Clustering is beneficial to discover meaningful subgroups and latent patterns in a data set (Han et al., 2011) and to classify samples into many groups using an association measure for exploring clusters with the highest inter-group distances and intra-group similarity (Kantardzic, 2011). In the study, k-means clustering algorithm was performed to explore different profiles of the learners based on their interaction data in terms of using LMS tools. K-means clustering algorithm that assumes Euclidean space can be used for finding clusters in the data set, where the groups are identified by their cluster centers which are the typical representatives of the groups (Alpaydin, 2009). This algorithm enabled researchers to reveal different profiles of online learners based on their interaction with LMS tools. Similarly, several researchers have explored online interaction patterns of learners using k-means clustering algorithm as an educational data mining method (Cerezo et al., 2016; Lust et al., 2011). Before k-means clustering analysis, hierarchical clustering analysis was employed to decide an optimal number of clusters in the data set considering the dendrogram as recommended by Zhou et al. (2017). The Calinski–Harabaz (CH) index was used to determine to evaluate k-means clustering algorithm in the study. Additionally, a one-way ANOVA with Tukey post hoc test was conducted to determine whether the learners in the clusters differ from each other and validate the analysis.

Results

Clusters constructed through the learners' interaction behaviors on LMS tools

The correlations between SRL scores and the number of interactions with tools in Moodle are presented in Table 3.

Table 3 shows that goal setting is positively correlated with assessment interaction ($r=0.447$, $p<0.01$). However, goal setting has a negative correlation with forum interaction ($r=0.475$, $p<0.01$), content interaction ($r=0.447$, $p<0.01$), assignment interaction ($r=0.447$, $p<0.01$) significantly. The self-evaluation is positively correlated with assessment interaction ($r=0.437$, $p<0.01$) but it has a negative correlation with forum interaction ($r=-0.599$, $p<0.01$), content interaction ($r=-0.540$, $p<0.01$), assignment interaction ($r=-0.369$, $p<0.01$), chat interaction ($r=-0.487$, $p<0.01$), survey interaction ($r=-0.383$, $p<0.01$) and glossary interaction ($r=-0.318$, $p<0.05$) significantly. The environment structuring showed a statistically significant relation to content interaction ($r=0.318$, $p<0.05$) and

Table 3 Descriptive statistics and correlation analysis results

SRL dimensions	Assessment	Forum	Content	Assignment	Chat	Survey	Glossary
Goal setting	0.447**	– 0.475**	– 0.409**	– 0.318*	– 0.330*	– 0.250	– 0.214
Self-evaluation	0.437**	– 0.599**	– 0.540**	– 0.369**	– 0.487**	– 0.383**	– 0.318*
Environment structuring	– 0.166	192	0.318*	0.250	0.023	0.140	0.260*
Task strategies	– 0.043	0.046	0.020	0.107	0.149	0.046	0.051
Time management	– 0.132	0.201	0.186	0.239	0.124	0.060	0.066
Help-seeking	0.011	0.094	0.162	0.272*	0.172	0.136	0.156
Mean	80.58	98.91	152.76	15.88	11.18	13.25	6.73
SD	57.24	79.26	112.42	11.68	6.11	4.71	8.25
Minimum	3	10	11	1	5	1	1
Maximum	209	301	450	29	30	25	42

**$p<0.01$, *$p<0.05$

glossary interaction (r = 0.260, $p<0.05$). The help-seeking is positively correlated with assignment interaction (r = 0.272, $p<0.05$). The task strategies and the time management did not show statistically significant relation to all interaction variables.

SRL skills of the online learners reflected on the clusters

A k-means clustering analysis was conducted to identify subgroups of the learners with similar patterns. The cluster analysis results showed that a three-cluster solution was explored based on the value of the squared Euclidean distance between clusters. The clustering analysis results are shown in Table 4.

Table 4 indicates that the learners were profiled based on their interaction behaviors into three groups: Cluster 1 (*Actively engaging*, N = 16), Cluster 2 (*Assessment-oriented*, N = 27), and Cluster 3 (*Passively engaging*, N = 17). Learners in Cluster 2 engaged more frequently with assessment activities than those in the other clusters.

Table 4 Summary statistics of the three-cluster solution

Variables	Cluster 1 (N = 6) mean	Cluster 2 (N = 27) mean	Cluster 3 (N = 17) mean	F	*p*	Effect size (η^2)
Assessment interaction	72.06	107.70	45.53	7.88	0.00	0.21
Forum interaction	201.63	30.67	110.65	114.60	0.00	0.79
Content interaction	304.44	62.04	154.12	108.31	0.00	0.78
Assignment interaction	29.25	8.59	14.88	32.85	0.00	0.53
Chat interaction	16.44	7.74	11.71	15.16	0.00	0.34
Survey interaction	17.75	10.63	13.18	18.15	0.00	0.38
Glossary interaction	16.13	2.48	4.65	27.53	0.00	0.49

Learners in Cluster 1 were the most active learners who interacted with course contents and forum/discussion activities more frequently. Learners in Cluster 3 moderately engaged with all learning resources and activities. Significant differences were also found among the three clusters in all interaction variables with a large effect size of Eta squared according to Cohen's (1988) guidelines ($\eta^2 > 0.138$).

To determine whether the learners in the clusters differ from each other concerning their SRL skill scores, a one-way ANOVA with Tukey post hoc test was conducted. Table 5 shows the one-way ANOVA and post-hoc test results.

As shown in Table 5, the clusters differed significantly in their scores of goal setting ($F(2,57) = 44.26$, $p < 0.001$, $\eta^2 = 0.60$) and self-evaluation ($F(2,57) = 52.57$, $p < 0.001$, $\eta^2 = 0.64$) with large effect sizes. Environment structuring ($F = 1.957$, $p > 0.05$), task strategies ($F = 0.31$, $p > 0.05$), time management ($F = 1.35$, $p > 0.05$) and help-seeking ($F = 0.65$, $p > 0.05$) did not have statistically significant contrasts between the three clusters of learners with scores. The Tukey results showed that Cluster 2 was able to get higher goal-setting scores statistically significantly further than Cluster 1 and Cluster 2 group learners had significantly higher goal-setting scores than Cluster 3. While there was no statistically significant difference between the self-evaluation scores of Cluster 1 and Cluster 3, the significant difference in self-evaluation scores was derived from the self-evaluation scores of Cluster 2 which is significantly higher than both of the two groups; Cluster 1 and Cluster 3.

As an interesting result, the learners in Cluster 2 had the highest scores in goal setting and self-evaluation, while the lowest score was in environment structuring and task strategies. Learners in Cluster 1 had the highest scores in environment structuring, task strategies, and help-seeking. They had relatively lower scores in goal setting and self-evaluation. Also, they had relatively lower scores in environment structuring, task strategies, and time management scores compared with the learners in the other clusters. Concerning sub-skills, while the learners in Cluster 3 had the lowest scores in goal setting, self-evaluation, and help-seeking, the time management skills, environment structuring, and task strategies scores are the

Table 5 ANOVA results on SRL sub-skills scores among the clusters

	(1) Actively engaging (N = 16)		(2) Assessment oriented (N = 27)		(3) Passively engaging (N = 17)		ANOVA	Post-hoc test (Tukey)	Effect size (η^2)
SRL Skills	Mean	SD	Mean	SD	Mean	SD	F		
Goal setting	9.87	3.32	17.85	4.47	7.17	3.45	44.26*	2 > 1 2 > 3	0.60
Self-evaluation	6.43	2.63	14.51	3.63	5.76	2.81	52.57*	2 > 1 2 > 3	0.64
Environment structuring	16.31	2.52	14.11	3.88	14.94	3.71	1.95	–	–
Task strategies	12.5	3.52	11.66	3.94	11.82	2.48	0.31	–	–
Time management	8.68	2.27	7.44	2.83	8.29	2.22	1.35	–	–
Help-seeking	13.5	2.89	12.51	3.46	12.29	3.27	0.65	–	–

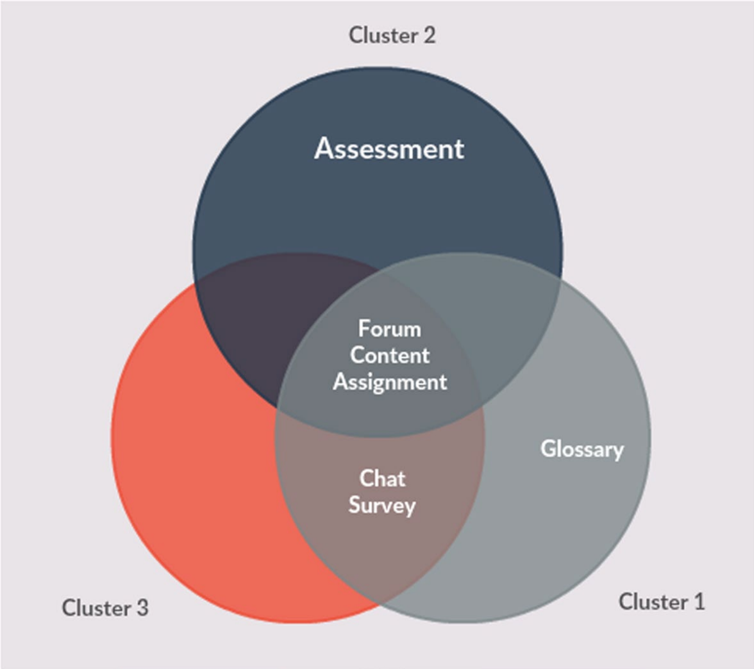

Fig. 2 Clusters and mostly used LMS tools

lowest among Cluster 2 learners. Cluster 1 learners mostly had the highest scores in the sub-skills except for two (goal setting and self-evaluation).

Both Tables 3 and 4 illustrate that while some of the Moodle tools are prominent in discriminating learners' SRL skills, some others are not remarkable. Figure 2 visualizes this association between Moodle tools and SRL skills.

Figure 2 indicates that assessment plays a discriminative role for three clusters. Surprisingly, forum, content, and assignment components are commonly used by all clusters. Namely, these components are not decisive for profiling learners, but they can influence the clustering through their usage frequencies.

Discussion

This study explored the learners' profiles through their interaction behaviors in Moodle about SRL skills. SRL skills have been taken into consideration through Zimmerman's model. We found that goal setting and self-evaluation were associated with the interaction behaviors of online learners significantly. Remarkably, there were significant correlations between assessment interaction and three self-regulation skills goal setting, self-evaluation, and help-seeking. These results further support the idea of contextualizing interaction data derived from learners' online learning behaviors to explore their self-regulation patterns (Cicchinelli et al., 2018; Jovanović et al., 2017).

The clusters constructed through online learners' interactions

It will be insightful to explore the LMS tools playing a discriminant role in the profiling of the learners into three clusters. It was found that assessment, forum, and content tools were important for the clusters. This result supports other studies in this field linking learners' interaction with online learning tools with online learning experience (Kokoç & Altun, 2019; Cerezo et al., 2016; Li & Tsai, 2017). In this sense, Kokoç and Altun (2019) revealed that the learners' interaction with assessment tools is an important component of their online learning experiences. The fact that most of the participants can be profiled based on their interaction with the assessment tool came to the forefront of the study. A possible explanation for this result may be the dominant role of the quizzes that were used in the LMSs. In the study, various types of questions were used in the quizzes to measure the learning performances of the learners. Learners might use these tools to determine their comprehension regarding course materials or assignments. Thus, they check their progress and try to adapt their learning for necessary situations. On the other hand, the online learners interacted with assessment activities based on a specific learning task asked by the instructor. One can infer that the online learners profiled based on the assessment interaction can be assigned as assessment-oriented learners.

It is seen that a survey is a common tool for both of the clusters to be actively engaged, passively engaged, and assessment-oriented. Considering the nature of the surveys prepared by the instructor, it is seen to be inevitable for learners dealing with instructor-oriented tools. Similarly, Cerezo et al. (2016) explored different patterns of learners' interaction with the LMS and profiled learners into four clusters, namely, non-procrastinators, socially focused, individually focused, and procrastinators. In addition, even if learners are alone in the learning process and should have high SRL skills, sometimes they need someone to trigger their deal with the course. At this point, surveys may be put in place to support SRL skills. Assessment tool which has higher interactions than others came to the forefront in this study, which may be due to the learners in all clusters who can use these tools that contribute positively to the evaluation-based SRL skills, which results in some learners in these clusters being goal-oriented learners. The assignment tool in this study also supported the learners who have high help-seeking skills in the process of doing homework and seeking help from different sources in the process. In this study, the assignment tool appears as a functional tool that needs to be employed to increase learners' help-seeking skills. Similarly, another study pointed out improved help-seeking skills because of the importance of improving these skills in online learning environments (Chou et al., 2018). They found that one of the important differences in the clusters is the groups being separated about the learners' task-oriented and non-task situations. Similarly, in the current study, some online learners tended to experience task-oriented learning during the process. The frequency of interacting with other online tools such as forums, content, and assignments was prominent in forming clusters. Surprisingly, while these tools are frequently used by actively engaged and passively engaged learners, assessment-oriented learners use these tools less frequently. This finding is in accord with the studies in which the clusters were assigned through the frequencies of using learning resources, accessing the tools, and the level of interaction together (Khalil & Ebner, 2017; Li & Tsai, 2017). At this point, some researchers argue that online learners engaging in assessment activities such as quizzes mostly desire to receive feedback about their learning extents rather than getting informed about the learning process (Verbert et al., 2014).

SRL skills reflected on mostly used LMS learning tools

The results highlight that there was a reflection of learners' result-oriented approaches to learning processes. A statistically significant difference between the goal-setting and self-evaluation scores of the online learners in Cluster 2 and other learners' scores in the other clusters was found. This result supports the claim that learners' interaction with tools in online learning is associated with the online self-regulation skills of learners (Pérez-Sanagustín et al., 2018). This may also be explained by the relationship between goal setting and self-evaluation in a theoretical sense. Thus, online learners with higher goal-setting skills set specific learning task goals and plan their process toward achieving them (Onah & Sinclair, 2017) while online learners with higher self-evaluation skills are aware of their learning behavior and judge their learning performances and outcomes according to their learning goals (Alonso-Mencía et al., 2020). Goal setting has a positive relationship with assessment interaction, while it has a negative relationship with content interaction, forum interaction, and assignment interaction. Online learners with higher goal-setting levels define their learning goals and strategies to achieve them in the online learning environment (Alonso-Mencía et al., 2020). In addition, they are more likely to attain their goals and consider measurable learning outcomes such as quiz results, and exam points rather than learning activities (Kizilcec et al., 2016). Thus, one can infer that learners' high-level assessment interaction is appropriate for the nature of the goal setting. Remarkably, goal setting has a negative relationship with forum interaction, content interaction, and assignment interaction. This result is contrary to previous studies which have suggested that collaborative and communication tools and content creation or delivery tools in LMSs also support goal-setting skills of learners in the online learning process (Dabbagh & Kitsantas, 2013; Wong et al., 2019).

It is interesting to note that there are some other issues affecting the interaction behaviors in Moodle. Our study revealed that using quizzes is associated with higher goal-setting and self-evaluation skills of learners. This result is in line with the study of Kizilcec et al. (2017) who revealed that learners with stronger goal-setting and self-evaluation skills were more likely to visit assessment activities and spend more time on assessments. Similarly, Yang and Tsai (2010) concluded that assessment activities may develop SRL-related skills of learners. The nature of the online course can also be thought to influence the development of time management and help-seeking skills. The interaction frequency of the chat glossary and survey tools was the lowest when compared to the other tools. At this point, because the interaction of the learner-learner or learner-lecturer was low, the frequency of using this chat tool was low.

Conclusions and recommendations

The results indicated that content, assessment, forum, chat, and assignment components are seen as important for environment structuring, task strategies, time management, help-seeking which cover Cluster 2, namely, the assessment-oriented group. Thus, instructors may pay attention not to ignore the assessment-based activities and to take care of making learners use these tools. On the other hand, the findings of the prior studies presented that someone interacting less with the LMS tools has the potential to drop out or have less academic achievement. This study provides hints that one reason for the improvement of online learning performance may be using SRL strategies derived from interacting with the tools.

The findings about the interaction with the LMS tools may present new insights into how learners regulate themselves in their online learning journeys. The study will extend previous research by covering some aspects of students' experience, including their interactions using online learning tools, as well as the links between the tools and their regulation skills. By taking profiles into account, educators could provide meaningful design for learners by referring to the answer to the question of what tools they use to do what. Thus, instructional designers should take care of the affordances of the LMSs which can prioritize learner needs and instructors should encourage learners to monitor their interactions and go on the journey.

The study has several limitations that should be noted. First, the sample size was small, and the instructional unit was specific. The selection and size of the study subjects may limit the generalization of the study findings. Another limitation is the tools of Moodle, 7 of which were analyzed for supporting self-regulation in online environments. So, a larger sample size and more tools would increase the sensitivity of the analysis and the construction of the clusters. This study also confirmed that data from online environments that capture learners' actual interaction behaviors are interrelated with the data from self-report instruments (Bannert et al., 2014; Ellis et al., 2017).

In sum, the most often used components of Moodle were found as assessment, forum, content, and assignment. Thus, future studies may focus on developing how the LMSs support interacting more with these tools. The functional tools considering the nature of the SRL strategies may be integrated into the LMSs. Further studies can suggest interventions regarding these tools. To conclude, we hope that the findings of this study will assist in the future design and implementation of log-based profiling and behavior analysis studies for LMSs.

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