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Longitudinal Analysis of Reciprocal Relationships between Digital Literacy and Self-Regulated Learning within Personal Learning Environments

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Completed Research Paper

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Abstract

Personal learning environments (PLEs) offer valuable opportunities to enhance overall learning experiences while nurturing technological and learning skills of contemporary learners. To maximize these opportunities researchers and practitioners must clearly understand how learners' digital literacy (DL) and self-regulated learning (SRL) skills are interrelated within PLEs. This paper presents the quantitative findings of an ongoing longitudinal mixed methods study designed to identify and describe these relationships. Structural equation modeling is used to test competing two-wave panel models using online survey data from 181 participants. The results support the acceptance of a model with significant positive reciprocal relationships between DL component constructs and the SRL construct. We contribute, via empirical evidence, to clarifying the direction and extent to which DL and SRL skills of undergraduates influence each other within PLEs. The paper concludes with a discussion of the implications for theory and practice together with future research opportunities.

Keywords: Personal learning environments, longitudinal panel model, reciprocity

Introduction

Personal learning environments (PLEs) are transformative learning spaces. They provide an innovative learner-centric approach to technology-enhanced learning (TEL) and a practical approach for organizing all the different ubiquitous devices, tools and technologies contemporary learners use in their everyday life for personalized learning. Components and content of student-centered and created PLEs are adopted and adapted to fit individual learning needs, rarely limiting to a single technology, device, application or activity (Hricko 2017).

Self-regulated learning (SRL) within a social-cognitive perspective is defined as the deliberately generated thoughts, feelings, and actions that are repetitively adapted for attaining personal learning goals. It is a cyclic interaction of the person (self), the behavior (action) and the environment within three successive phases of (1) forecasting (processes preceding the learning effort), (2) execution-control (processes occurring during learning) and (3) self-reflection (processes that occur after learning) (Zimmerman 2000). PLEs support regulation of self, behavior, and environment via collecting, planning, monitoring and adapting independent learning tools and resources to realize an explicit learning goal. Thus, SRL is regarded as an essential characteristic of the PLE, enabling learners to remain attentive, motivated, and engaged in learning tasks (Melzer and Schoop 2015).

PLEs are also regarded as a context for developing digital literacy (DL) skills (Laakkonen and Taalas 2015). DL is the collection of literacies associated with the usage of digital technologies including desktops, mobile devices (e.g. laptops, tablets, smartphones, PDAs), Web 2.0 tools and other collaborative resources on the internet as well as any open source or commercially available software packages, for learning. The associated multiple literacies consist of: photo-visual literacy; reproduction literacy; branching literacy; information literacy; socio-emotional literacy and real-time thinking skill (Eshet 2012). These are incorporated into three components of DL (Ng 2012), consisting of (1) technical literacy (TL) defined as technical and operational skills needed to competently use digital technology, (2) cognitive literacy (CL) defined as cognitive skills used in information search, retrieval skills using technology and knowledge on related ethical, moral and legal issues, and (3) social-emotional literacy (SEL) defined as the literacy associated with the emotional and social aspects of online socializing, collaborating, evaluating information, and using digital technology for collaborative knowledge construction.

DL is an area which has been criticized for its lack of comprehensive integrative frameworks and theoretical foundation, as the discourse in this area is mainly practice-oriented. While researchers imply that DL could have a much deeper link to the learning strategies and particularly SRL skills of students, empirical evidence is lacking (Prior et al. 2016). Moreover, most prior studies in the area are cross-sectional and employ an experimental approach imposing particular technologies on the research participants, and do not investigate how the current PLE used in daily life and DL and SRL skills gained herein could be interrelated. Although there is some general agreement that these are interrelated, the nature, magnitude and the causal direction of the relationships between DL and SRL within PLEs is not yet clarified. As such prior studies are unable to provide sound empirical evidence of how DL and SRL skill interaction takes place within user controlled and managed informal PLEs, even though the creation of such PLEs is a prevalent learning strategy among contemporary learners.

The objective of this study is to use longitudinal data to explore the direction and causal nature of the relationships between DL and SRL skills of a representative sample of undergraduates, within the context of their technology-based informal PLEs. The study reported in this paper is a component of a broader longitudinal mixed methods study as discussed in Perera Muthupoltotage and Gardner (2018) with the overarching research question '*To what extent and in what ways are the DL skills and SRL skills of students interrelated when using an informal PLE?*' Findings of this study will augment the ongoing discussion among Information Systems (IS) researchers on understanding technology use and the role of technology in teaching and learning as well as skill development by providing insight on the causes and effects of DL skills developed and fostered through the informal use of technology via PLEs. The results would also deepen our understanding of how academic self-regulatory behaviors could vary as a result of interaction with technology for learning and digital skills developed herein, creating a more precise picture of the interrelationships between DL and SRL constructs within PLEs. Hence, practitioners could be enabled in appropriately considering the role of these skills as well as how best to nurture them when creating frameworks for adoption and diffusion of informal PLEs in teaching and learning tasks.

A discussion of background, research model, and hypothesis, research method employed in this study and results of the investigation follows. The paper concludes with its contributions and directions for future research.

Personal Learning Environments (PLEs)

PLEs are multidimensional systems which enable learners to control the content and process of learning by selecting digital resources, applications, and activities which best serve their individual learning needs. The core concepts of these dynamic learning spaces are self-regulation and adaptation to personal needs (Hricko 2017). It is an inherently individual environment where no universal model is possible and consists not only of the technological tools, but also individuals' digital identity, relationships and multiple interactions with other individuals. Thus the strength of these environments is that they can bring together the previously separate sources and contexts of learning. By including frequently used technologies and tools for taking responsibility of own learning and providing a natural connection between formal and informal learning, PLEs provide an opportunity for learners to develop the skills and literacies needed to effectively use emerging technologies in a rapidly changing society (Oliveira and Morgado 2016). However, research indicates some challenges of adopting PLEs effectively for learning in higher education including difficulties in unifying multiple environments toward a common learning objective and the learners lack of necessary skills (Johnson and Sherlock 2014). Given this confusing current research landscape of predicted opportunities vs. challenges, it is imperative to empirically evaluate the actual usage of PLEs and skill development within them.

Research Model and Hypotheses

Technical, cognitive and social-emotional skills of the technology users are a prerequisite and logical determinant for effectively using any technologies for learning tasks (Tang and Chaw 2016). An early literacy framework proposed by Beetham et al. (2009) theorized that a highly digitally literate student could be better at regulating their learning activities via the use of technology than a less digitally literate counterpart. More recent research affirms that the technological skills gained via constant use of technology can foster SRL in higher education contexts (Dabbagh and Kitsantas 2012). Other studies (e.g. Goh et al. 2012; Kauffman et al. 2011) have indicated that the persistent use of technology impacts how SRL skills are developed and nurtured. Yet more studies have clearly evidenced that diverse technological tools effected the implementation of some SRL processes (Yot-Domínguez and Marcelo 2017). Much of this existing research, however, focuses on investigating the SRL processes and actions of students with relation to specific technologies and narrowly consider the capabilities of the technology in itself. Studies of how technological fluency affects SRL within learning environments using multiple tools and technologies are infrequent. But, recent research conducted within a university e-learning environment posit a strong positive relationship between DL and SRL skills of learners (Yang and Kim 2014). Nevertheless, research investigating DL as an antecedent for how well learners regulate their learning is still lacking. But, holistically considering the previous research it can be argued that DL acts as a determinant of how well learners are able to regulate their learning in TEL environments such as PLEs. Thus, we hypothesize that *DL at Time 1 positively influences the SRL skills of students at Time 2. (H1)*

Additionally, research indicates that DL requires effective SRL. SRL processes enacted while learning with computer-based digital tools have been comprehensively documented (Greene et al. 2014). Aspects of self-regulation in learning are also thought to be component skills in some digital literacy definitions, indicating that in order to develop DL skills; SRL skills are antecedent. Successful intervention studies detail the promotion of DL as part of a larger focus on students' SRL (Jung and McMahon 2012). In view of this prior research, and the cyclic nature of SRL, self-regulated learners could plan and monitor learning actions performed on and via the PLE and upon reflection take appropriate behavioral action for applying and furthering DL skills to enhance the learning experience within the PLE. The SRL capabilities of the student, therefore, could have a positive influence on how well he /she applies DL skills for the learning task. As proposed by Valentín et al., (2013) this relation between SRL strategies and digital skills may even be casual. Consequently, we hypothesize that *SRL at Time 1 positively influences DL of students at Time 2. (H2)*

Finally, there is reason to believe that the relationship between SRL and DL is reciprocal, as suggested by some authors (e.g. Besbes, 2016; Steiner et al., 2013). This reciprocal relationship is best understood via the consideration of a commonly occurring learning scenario among contemporary learners. Consider an undergraduate using online search tools (e.g. a web-based search engine) of their PLE for accessing further information related to a particular subject, previously discussed in class. In order to maximize learning, he/she should be able to effectively plan the search task to increase usefulness and relevance of information, data, videos or interactive simulations obtained via the Internet. The learner would possess some ability to monitor and evaluate the impact of these resources on his/her knowledge. Reflecting on how the information received augments current knowledge, and organizing subsequent learning activities accordingly should also be done. At each stage, the learner may well utilize various components of their PLE (e.g. planning and scheduling tools, resource management tools, word processing tools). The learner may even discuss the information obtained with peers via social networks and communication tools integrated into to the PLE, seeking their assistance for enhanced understanding. These activities of (i) planning, (ii) cognition, (iii) monitoring, and (iv) regulating are component skills of SRL (Zimmerman, 2000). Moreover, in terms of DL skills necessary for completing the learning task successfully, the learner needs to competently use the web-based search tools and other communication tools (i.e. technical literacy). He/she should critically evaluate and select the information required while being knowledgeable of related ethical, moral and legal issues related to web-based activities such as plagiarism (i.e. cognitive literacy). Observing 'netiquette' while avoiding misinterpretation and misunderstanding and showing an awareness of privacy and individual safety concerns (i.e. social-emotional literacy) is also relevant here.

Without successfully applying both DL and SRL skills the learner would not be able to complete the learning task effectively via his/her PLE. However, at a conceptual level, it can be argued that learners' level of DL in terms of ability to select and effectively; yet ethically use technology, would consequently influence how well the learner is able to engage in the above SRL activities. Moreover, how skilled the learner is in regulating his/her own learning could subsequently influence how well the learner is able to demonstrate technical, cognitive and social-emotional literacy when engaging with technology within the PLE. Therefore we finally hypothesize that *DL and SRL mutually influence each other (H3).*

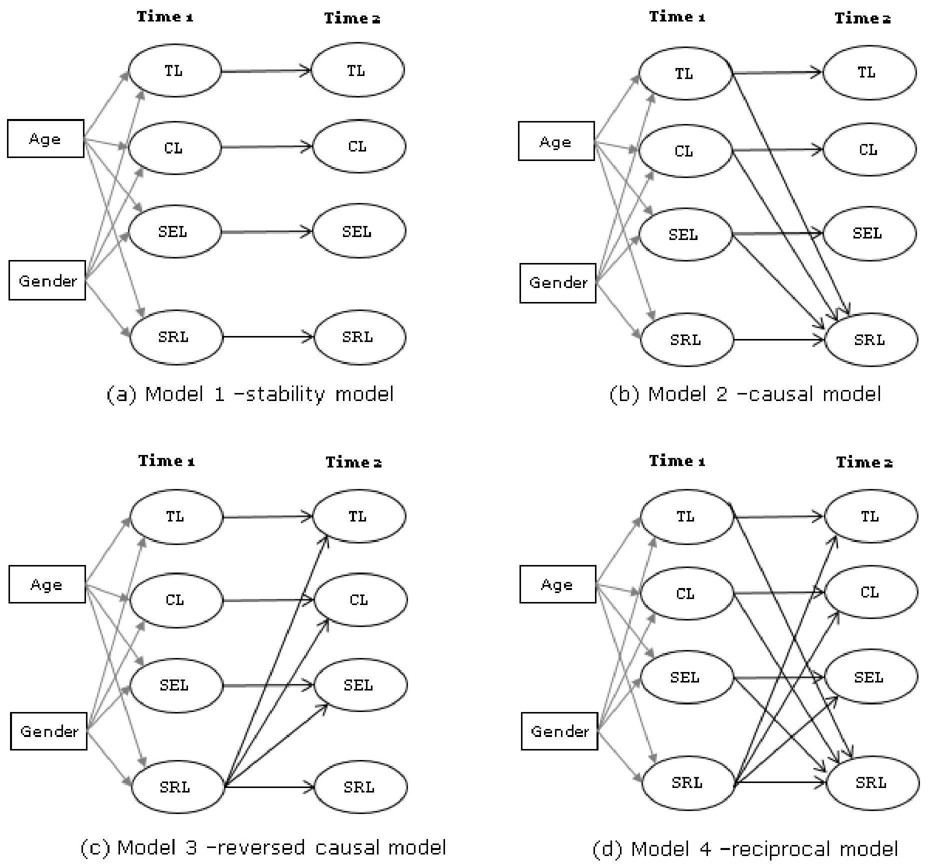


Figure 1. The Hypothesized Structural Models

This study examined these hypotheses using several cross-lagged panel models of the relationship between DL constructs and SRL skills, controlling for the effects of age and gender as seen in Figure 1. In the first stability model (Model 1 in Figure 1 above), we suggest that DL and SRL do not influence each other directly but share variance caused by unmeasured factors, therefore only the auto-regressive effects of each variable across the two waves are specified. Then, this stability model was compared with the three other models in Figure 1. The second model (Model 2 in Figure 1), specified cross-lagged structural paths from Time 1 TL, CL, and SEL to Time 2 SRL, reflecting hypothesis H1. The third structural model (Model 3 in Figure 1), is a reversed causal model specifying cross-lagged structural paths from Time 1 SRL to Time 2 TL, CL, and SEL, reflecting hypothesis H2. The fourth is a nested model of the previous two, (Model 4 in Figure 1) and indicates reciprocal relationships between the DL component construct and SRL construct reflecting hypothesis H3.

The purpose of this paper is to compare the relative fit of these competing models and select the best fitting model. Such an analysis would help clarify the nature and magnitude of the relationships among these constructs and their pattern of change over time complementing our current understanding of digital disruption caused by educational technology use as well as resultant opportunities.

Method

Participants, Procedures, and Materials

The participants consisted of a random sample of 181 first-year undergraduate students enrolled in courses within the Business faculty of a top university in the Asia-Pacific region. Data collection was performed using online surveys via Qualitrics. In the first phase of data collection, the survey was emailed to participants in July 2016 and the respondents asked to indicate willingness to participate in the second follow up survey. Respondents who agreed to continued participation in the research were emailed the survey again for the second phase of data collection in March 2017. Due to lack of prior research in this area, yet, there is no clear basis for specifying the appropriate time lag between variables. The interval we used between the two measurement points was 8 months. This accounted for capturing data points across two academic years for the participants. The gender distribution revealed more females than males (59% vs. 41%). The sample's age ranged from 16-30 years with a mean age of 19 years (SD = 2.007), while 79.8% were between 18-20 years old.

Both measurement scales for DL and SRL were 5 point Likert scales ranging from 1 'strongly disagree' to 5 'strongly agree'. Measurement scales for DL were drawn from the instrument used by Ng (2012) consisting of 1) technical literacy (TL) (6 items), 2) cognitive literacy (CL) (2 items), 3) social-emotional literacy (SEL) (2 items). In this study, the scale demonstrated internal consistency reliabilities of $\alpha = .956$ at Time 1 and $\alpha = .867$ at Time 2, and a test-retest reliability of .902 ($p<=0.001$).

The seven-factor structure from the academic SRL scale (Magno 2010) was used for measuring self-regulated learning. It consisted of (1) Memory strategy (14 items), pertaining to strategies used for memorizing and retaining information. (2) Goal-setting (5 items), involving setting specific proximal goals for oneself. (3) Self-evaluation (12 items), is the constant reflection on and rectification of one's learning methods for achieving learning goals. (4) Seeking assistance (8 items), is actively obtaining help from outside resources to supplement learning including teachers or peers as well as digital resources. (5) Environmental structuring (5 items), is restructuring one's physical and social context for compatibility with one's learning goals. (6) Learning responsibility (5 items), is ascribing causation to results and adapting future methods. (7) Organizing (6 items), involves monitoring performance selectively for signs of progress while efficiently managing time. In this study, the scale demonstrated internal consistency reliabilities of $\alpha = .988$ at Time 1 and $\alpha = .924$ at Time 2, and a test-retest reliability of .972 ($p<=0.001$). Usage ratings and perceptions of the usefulness of various technologies used in the PLEs were also surveyed. To ensure face and internal validity as well as consistency, a pilot test was conducted among 18 first and second-year undergraduate students, 5 postgraduate students and 2 academic staff members before survey items were released via email to the target population.

Model Testing

Structured equation modeling (SEM) technique, was used for statistical analysis. SEM enables characterization of real-world processes better than simple correlation-based models. Using SEM to compare models enabled the examination of autoregressive effects that describe the stability of DL and SRL across different time points, while simultaneously examining hypothesized effects of one construct on another across time. Thus, while being consistent with the recommendations of Farrell (1994) for evaluating reciprocal relations, bias in estimating hypothesized cross-lagged effects are also minimized.

Due to the large number of items used to operationalize the higher order SRL construct, as a first step in the analysis, the reliability and validity of the primary-order factor structure of the academic SRL scale was examined for each wave of data collected using confirmatory factor analysis (CFA) with AMOS Graphics 24.0.The indicator loading of each indicator on its relevant SRL construct together with model fit indices for each wave were examined. For both waves of data, acceptable model fit was achieved for the primary-order structural models at each wave, (Wave1 CMIN/DF = 2.101, CFI= 0.907, GFI = 0.91; Wave 2 CMIN/DF =2.429, CFI= 0.943, GFI = 0.903). Next, imputed factor scores from the primary-order factor models were used for including the SRL second-order latent construct in the construction of a measurement model for all latent constructs. The measurement model consisted of three latent constructs for DL and seven second-order latent constructs for SRL at each wave. The measurement model validity and reliability was investigated and established (see Table 1).

Table 1. Validity and Reliability of Constructs

Correlations	TL1	CL1	SEL1	SRL1	TL2	CL2	SEL2	SRL2
TL1	**0.873**							
CL1	0.847***	**0.917**						
SEL1	0.798***	0.782***	**0.932**					
SRL1	0.069	0.033	0.082	**0.706**				
TL2	0.138*	0.15	0.147	0.202*	**0.82**			
CL2	0.032	0.035*	0.016	0.319***	0.46***	**0.863**		
SEL2	0.125	0.134	0.109*	0.417***	0.36***	0.391***	**0.819**	
SRL2	0.683***	0.607***	0.60***	0.116*	0.18	0.104	0.115	**0.855**
Age	0.043	0.088	0.017	-0.04	0.125	-0.012	0.029	0.042
Gender	-0.124	-0.066	-0.099	-0.093	-0.083	0.015	-0.172	-0.087
Validity indicators								
Composite Reliability	0.951	0.914	0.929	0.874	0.925	0.854	0.802	0.95
Cronbach α	0.938	0.812	0.848	0.831	0.902	0.697	0.707	0.938
AVE	0.763	0.842	0.868	0.502	0.672	0.745	0.67	0.732

Note: TL1 indicates TL construct at Time 1 and TL2 indicates TL construct at Time 2, etc.
* p < 0.1, ** p < 0.05, *** p < 0.001, Square root of AVE shown in bold

Next, imputed factor scores for SRL, TL CL and SEL were used for specifying four competing structural panel models, by including each construct as a latent variable. This approach is recommended for its ability to minimize problems of unreliable parameter estimates and insufficient power (de Jonge et al. 2001). Age and gender (coded 1 for Males and 2 for Females) were integrated as control variables in the models, assumed to be directly related to Time 1 variables and only indirectly at Time 2.

Model Comparison and Estimation

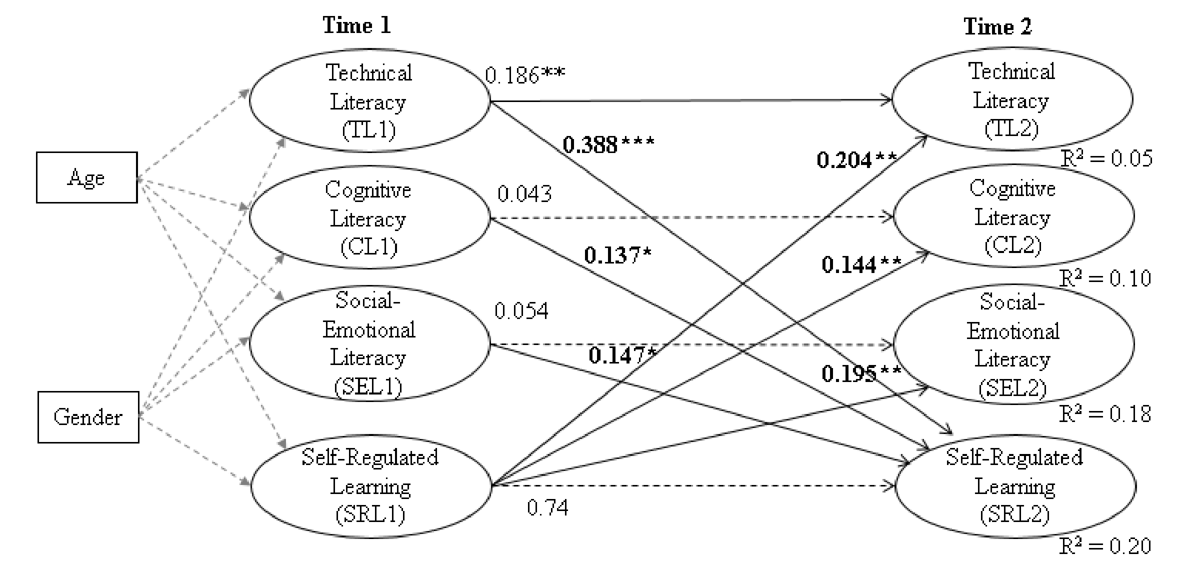
Chi-square difference test was used to compare the different nested structural models in separate analysis steps. An overview of model comparison is summarized in Table 2.

The first test indicated a significant ($p< 0.001$) difference between the stability model (Model 1) and the model with cross-lagged effects from DL to SRL. Therefore it was determined that the unconstrained model (Model 2) better accounts for the data than the constrained model with no lagged effects. Thus, there is statistical evidence that Time 1 DL constructs significantly influence SRL at Time 2. The second chi-squared difference test indicated that the unconstrained Model 3 also better accounts for the data than Model 1. Therefore statistically SRL at Time 1 can influence DL components at Time 2. When the stability model was compared with the reciprocal model with all cross-lagged structural paths (Model 1 vs Model 4), the test showed a significant improvement in model fit. Similarly, as seen in Table 3, Model 4 appeared to fit the data better than Model 2 and 3, in terms of chi-square relative to the degrees of freedom at a 99% confidence interval. The important fit indices for Model 4 (GFI = 0.901 CFI = 0.967, NFI = 0.837, AIC = 234.46, RMSEA = 0.07) revealed a relatively better fit according to criteria presented by Hu and Bentler (1999).

Table 2. Structural Model Comparison

Model	X2	df	Comparison	ΔX2	Δdf
Model 1	143.427***	53			
Model 2 (DLT1 -> SRLT2)	137.098***	50	Model1 vs Model2	6.329 p = 0.097	3
Model 3 (SRLT1) -> DLT2	135.917***	50	Model1 vs Model3	7.51 p = 0.057	3
Model 4 (reciprocal)	121.588***	47	Model1 vs Model 4	21.839 p = 0.001	6
			Model 2 vs Model 4	15.51 p = 0.001	3
			Model 3 vs Model 4	14.329 p = 0.002	3

The expected cross-validation index (ECVI) was also compared for the 4 models to determine the robustness of Model 4. As the sample of 181 subjects in the current study is not conductive for cross-validation, the single sample cross-validation method was adopted (Browne and Cudeck 1989). The 1.253 ECVI for Model 4 was lower than the ECVI values for Model 2 (1.611) and Model 3 (1.771). Thus, indicating a good fit for the data. Therefore reciprocal Model 4 better accounted for the data and is the more stable model. Rogosa (1979) recommends that once the existence of reciprocity is determined, the specific causal effects and the measures of strength of individual relationships should be examined. The standardized estimates for the structural paths of Model 4 are shown in Figure 2.



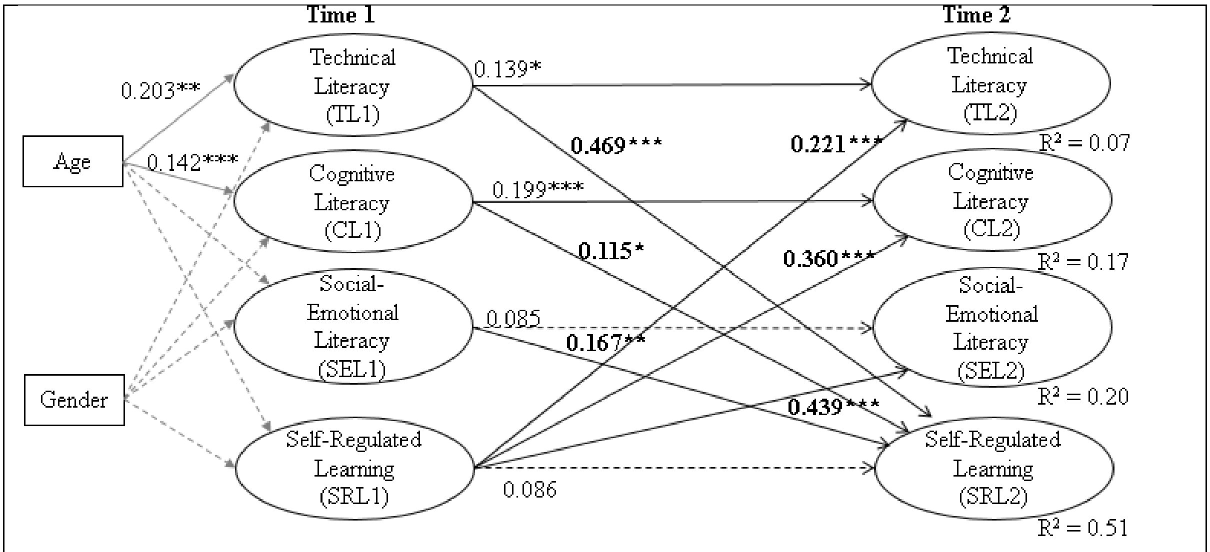
Note: * p<0.1 ** p < 0.05, *** p < 0.001. Dashed lines are insignificant relationships.

Figure 2. Standardized Estimates for the Final Longitudinal Structural Model (Model 4)

It is seen that SRL at Time 1 significantly influences DL components at Time 2. Further, higher levels of TL, CL, and SEL at Time 1 causes higher levels of SRL at Time 2. Thus the data supported the hypothesis that the DL and SRL constructs mutually influence each other (hypothesis H3).

The maximum likelihood (ML) based measures used above provide an overall test of model fit and enable the statistical comparison of nested models, but, the parameter estimates provided best explain the observed covariance. Therefore in predictive applications, there could be some loss of predictive accuracy. However, in a partial least square (PLS) based SEM approach parameters are estimated so as to maximize the variance explained in the set of latent variables. Therefore the covariance-based SEM approach (as performed by AMOS), and the PLS-based approach are advocated as complementary choices which depend on the purpose of the research (Anderson and Gerbing 1988). The ML-based approach is suitable for theory testing and model comparison while PLS is more suitable for application and prediction (Hair et al. 2016). Moreover, PLS-based SEM is thought to yield robust results regardless of sample size and normality issues (Chin et al. 2003) and is more suitable for exploratory work where the theoretical knowledge is relatively limited (Chin 2010); (Lowry and Gaskin 2014) as in the case of this study.

We used ML-based SEM for model comparison and found that Model 4 fit the data well. However, given the strong correlations between the latent variables, it was decided to further explore the reciprocal model to identify the key 'driver' constructs using PLS-SEM approach for a more rigorous analysis. The reciprocal Model 4 was evaluated using WarpPLS 6.0, Warp3 PLS regression algorithm, which tries to identify a relationship defined by a function whose first derivative is a U- curve, as found in most natural and behavioral functions (Kock, 2011a). After estimating p-values with both bootstrapping and jack-knifing resampling techniques, bootstrapping with 100 resamples was selected as the technique which provided the most stable coefficients. The results are summarized in Figure 3.



Note: * p < 0.1, ** p < 0.05, *** p < 0.001. Dashed lines are insignificant relationships.

Figure 3. PLS-SEM Estimates for Reciprocal Structural Model

The model performed acceptably well for the data with a Tenenhaus goodness of fit (GoF) of 0.326, where the proposed thresholds for the GoF are, small >= 0.1, medium >= 0.25, and large >= 0.36. While PLS path modeling naturally lacks an index of global validation of the model, the GoF provides an operational solution, as it can be used as an index for validating the PLS model globally. (Tenenhaus et al. 2005). The standardized chi-squared with 629 degrees of freedom (SChS) was 6.542, (P<0.001). Other model fit indices were also acceptable for the model as seen in Table 3.

In order to find the precise amount of variance that each antecedent, explains on a dependent construct in the selected model, we multiplied the path coefficient by the corresponding correlation coefficient and took the absolute value (Roldán and Sánchez-Franco 2012). The results are shown in Table 4.

According to the direct effects of the structural model, the TL1 (technical literacy at Time 1) is the construct that most significantly influences SRL at Time 2 (SRL2). There is also a strong positive linear relationship between the two constructs. The social-emotional literacy at Time 1 (SEL1), (direct effect = 0.18) was significantly positively associated with SRL2, even though the p-value is larger (p<=0.05). Positive direct association between the two variables CL1 (cognitive literacy at Time 1) and SRL2 (0.577, p<=0.001) can also be seen, but the direct influence of CL1 on SRL2 is insignificant (p-value = 0.1). The student's gender and age (respectively, p-values = 0.30 and 0.40) did not have a significant direct effect on SRL. TL1 and SEL1 explain 52% of the variation in SRL at Time 2 for the sample of undergraduates. 32% of this variance is explained by technical literacy. While the small p-value (≤ 0.001) indicates strong evidence to support this effect, the effect sizes of TL1 on SRL2 are within the small to medium range for the sample of undergraduates considered (Sawilowsky 2009).

Table 3. Model fit and Quality Statistics for the Reciprocal Model

Model fit and quality indices	Observed value	Expected value
Average block VIF (AVIF)	1.389	acceptable if <=5 , ideally<=3.3
Average full collinearity VIF (AFVIF)	2.179	acceptable if <=5 , ideally <=3.3
Sympson's paradox ratio (SPR)	1.000	acceptable if >=0.7 , ideally 1
R-squared contribution ratio (RSCR)	1.000	acceptable if >=0.9 , ideally 1
Nonlinear bivariate causality direction ratio (NLBCDR)	0.944	acceptable if >=0.7
Standardized root mean squared residual (SRMR)	0.081	acceptable if<=0.1
Standardized mean absolute residual (SMAR)	0.062	acceptable if <= 0.1

Table 4. R^2, Q^2 and Variance Explained for Significant Relationships in Reciprocal Model

	R^2	Q^2	Direct effect	Correlation	Variance explained
SRL2	0.515	0.514			
TL1 >			0.469 ***	0.683***	32%
CL1 >			0.115*	0.607***	7%
SEL1 >			0.167**	0.60***	10%
SRL1 > TL2	0.074	0.089	0.221***	0.202**	4%
SRL1 > CL2	0.166	0.173	0.360***	0.319***	11%
SRL1 > SEL2	0.205	0.212	0.439***	0.417***	18%
Note: * p < 0.1, ** p < 0.01, *** p < 0.001.					

Moreover, SRL at Time 1 (SRL1) was significantly positively associated with all three component constructs of digital literacy at Time 2. Social-emotional literacy at Time 2 (SEL2) was most heavily influenced (direct effect = 0.44, p<=0.001) by SRL1, followed by cognitive literacy (CL2) (direct effect = 0.36, p<=0.001). Technical literacy at Time 2 (TL2) was the least influenced by SRL1 (direct effect = 0.22, p-value = 0.02). 18% of the variation in SEL2, is explained by the SRL skills of the students at Time 1. When considering the linear relationship between the digital literacy constructs at Time 2 and their self-regulated learning skills at Time1, the positive association here appears to be mirrored by the direct influence of SRL2 on the three DL constructs. Age of the students was significantly related to TL and CL constructs at Time 1.Q^2 values greater than 0 for all the endogenous constructs indicate that this path model has predictive relevance (Hair et al. 2016). The Q^2 effect sizes indicate that TL, CL, and SEL at Time 1 have a large predictive relevance for SRL2. Similarly, SRL at Time 1 has medium to large predictive relevance for all DL components at Time 2.

Discussion

We used a two-wave panel design and empirical analysis applying SEM technique to examine the direction and extent to which SRL and DL constructs influence each other. The results support hypothesis H3 confirming that after controlling for age and gender DL and SRL constructs are reciprocally related.

Closely inspecting our results it is seen that SRL has a statistically significant positive effect on all components of DL. The largest effect is on Social- Emotional Literacy (SEL). SEL, in general, is a multidimensional construct that includes the ability to understand, recognize, and label one’s own and others’ emotions; appropriately express, control, and regulate one’s own feelings and behaviors; effectively establish, maintain, and manage social relationships; and make responsible choices and decisions (Nikolayev et al. 2016). SEL in relation to technology requires users to be highly critical and analytical, very mature, and have a good knowledge of socially acceptable behavior regarding collaborative technology use. This has been described as the highest-level and most complex of the digital literacy skills (Eshet 2012). The PLE, while individual in nature, provides opportunities for creating shared learning spaces (Liew & Kang, 2012). Collaboration with peers for learning tasks is an essential factor for SRL within PLEs, particularly for seeking assistance and environment structuring (Nussbaumer et al. 2015). Therefore how well a learner engages in these collaborative regulatory tasks within a PLE and skills gained herein, could well influence their subsequent abilities to demonstrate critical thinking, maturity and acceptable behavior when engaging with others using technology. SEL also influences the SRL level of our subjects at Time 2. Demonstrating responsible and acceptable behavior when connecting with others over the social tools, such as social networks of ones’ PLE is important to ensure ready and effective collaboration with peers (Conole 2013). The social-emotional skills honed in this manner, would then be put to use when engaging in collaborative SRL behaviors. The implications are also considerable in light of the concern that some authors express about lack of opportunities for contemporary learners to develop their social and emotional skills while relying on technology as their primary source of social interaction (Liew et al., 2010).

Technical literacy (TL), which involves possessing the applicable technical and operational skills to employ digital technologies for learning within PLEs, has a positive influence on SRL. A possible reason might be the prolific use of organizers and schedulers accessible on mobile phones and other devices integrated on to their PLEs for planning and management of their activities. Further, communication tools such as Skype and Messenger partnered with sharing mechanisms for artifacts produced such as Dropbox enables fast feedback on tasks together with seamless collaboration. Moreover, web-based formal an informal social network environments partnered with forums and blogs enable the restructuring of students’ social environment to suit their goals. Thus, the technical ability to use these tools effectively for learning will influence how well the SRL related activities such as planning and environment structuring will be executed. TL contributes to the overall success of the learning environment and our findings draw a parallel with prior studies which suggest that successful online learning environments may enhance learners’ self-regulation (Vighnarajah et al. 2009) The relationship between SRL and TL is reciprocal. There are several reasons why such a relationship may exist. The construction of a PLE involves the awareness of, experimentation with and selection of various tools which the learner feels will aid in their learning processes (Castañeda and Soto 2010). This involves the management of tools within the PLE, setting technology aided learning goals, initiating control and regularly monitoring, evaluating and structuring of the PLE environment. (Valtonen et al. 2012). These are SRL behaviors which have been shown to influence the level of initiative regarding PLE construction, where the level of initiative involves the ability to evaluate different tools for their technical capabilities and use them effectively (Yen et al. 2005).

In a prior study conducted using a case study approach , Willem, Aiello, & Bartolome, (2006) investigated if critical thinking towards the media was promoted through the acquisition of SRL skills in a technology-enhanced learning environment (TELE). They investigated various aspects of information literacy (i.e analyze and evaluate information, judge the reliability). It was seen that students used some SRL strategies influencing their information literacy. Given that information, literacy is an aspect of CL our findings that SRL significantly influences CL is in agreement here. Application of cognitive strategies such as rehearsal, elaboration, and organization are important aspects of being a self-regulated learner. They help students pay attention to the lesson, select important information and retain that information in memory (Sadi and Uyar 2013). The consistent use of such strategies using the tools of a PLE could possibly be fostering the information literacy and critical thinking skills which form the cognitive literacy component of DL. Our results indicate that this relationship between CL and SRL is also reciprocal. Searching, evaluation and organization skills honed via the use of PLE tools such as search engines and personal organizers, could be directly translated to strategies for evaluating information when learning both in and outside the classroom and organizing oneself as well as ones learning activities. The transferability of these cognitive skills could be the reason for the reciprocal relationships our results indicate.

To our knowledge, there are no other longitudinal studies conducted to investigate how DL and SRL constructs influence each other over time. However, with this study, we can add further empirical validity and clarity to the claims that the use of technology impacts SRL skills and show that SRL skills are influential in developing DL skills (Janssen et al., 2013; Shopova, 2014).

There are obviously other factors which could influence SRL skills within technology-enhanced learning environments. These range from technology-related factors such as service quality and usefulness of technologies (Zhao 2016) to user related factors such as technological anxiety, perceived technological self-efficacy and motivation (Liaw and Huang 2013). These and other factors could be moderators in the relationship of DL constructs on SRL within PLEs. Moreover, factors such as cultural settings, the digital divide, and infrastructure have also been shown to affect the digital literacy of undergraduates (Tuamsuk and Subramaniam 2017) and could again mediate or moderate the relationship between SRL and DL. Thus, more in-depth research is needed to examine the potential of these moderators and further test the significant relationships found in this study. The indirect effects of other variables such as proficiency levels in technology use and attitude towards learning with technology on the relationships between DL an SRL also warrant further investigation.

It must be noted that the maximum likelihood (ML) based measures used above provide an overall test of model fit and enable the statistical comparison of nested models, but, the parameter estimates provided best explain the observed covariance. Therefore in predictive applications, there could be some loss of predictive accuracy. The effects found in our analysis were moderate, yet, the findings are meaningful. Moreover, We acknowledge that passive longitudinal designs of the manner we have adopted as most suitable for the context of this study, do not enable researchers to isolate independent variables and experimentally control potentially confounding variables. Our objective is to observe the DL and SRL interactions within informal PLEs. Due to the inherent variability of such environments, it is impractical to attempt to control the variables of interests or other potentially confounding variables. Passive longitudinal designs are often used and thought to be necessary for such situations (Farrell 1994).

Conclusion

Our present findings, provide an opening for a comprehensive dialogue among researchers who are interested in understanding the patterns, contexts, and consequences of technology adoption for learning in informal PLEs. Theoretically, as very few longitudinal studies have been conducted to examine DL and SRL within PLEs our findings add to the literature in this area. Moreover, the explicit comparison of competing models as we have done carries more conviction than testing and failing to reject just one model. Further, the measurement model could confirm that the DL and SRL constructs we used demonstrate appropriate reliability and validity and could encourage other researchers in incorporating these constructs in their research. As we have not considered cultural attributes here, this research is ripe for replication in other cultural settings to determine if the relationships remain constant across different settings.

Practically, our findings indicate that learners are developing DL and SRL skills within the PLE frameworks that they create, in line with the constructivist learning environment paradigm where learners are said to make meaning of their own experiences (Jonassen and Land 2012). Teachers, institutions and other stakeholders should be sensitive to the possibility and the potential affordances that this creates for enhancing the learning experience and supporting skill acquisition and enhancement. PLEs are often criticized for their difficulty to be applied in educational settings as users may not have the technological fluency and self-regulatory skills necessary to create an effective PLE (Tu et al. 2015). Our findings can be used to develop evidence-based scaffolding programs for effective PLE creation as the reciprocity of DL and SRL suggest that the learners are teaching themselves the required skills.

Next, this exploratory analysis paves the way for further research. The survey data pertaining to usage and usefulness perceptions of various technologies consisting of the respondents PLEs must be analyzed to provide further depth to this analysis concerning reciprocity of skills. A qualitative analysis incorporating the examination of mind maps of actual PLEs constructed by students, combined with face to face semi-structured interviews could help in explaining and clarifying the above findings as well as identifying further factors which could influence this phenomenon. These analysis activities are presently underway and findings will be forthcoming.

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