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Social Media in Dynamic Learning:

Logistics and Influential Factors

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Abstract: *Educators have been using social media to enrich learning activities and promote interactive and collaborative learning. Under the context of dynamic learning – the way that 21st century's learners learn, the new challenges are: how educators design such a setting to effectively integrate certain social media tools to improve learning, and what the influential factors might be that educators need to focus during the design. In this article, we employ the concept "logistics" to explain and redefine dynamic design, dynamic learning, and dynamic thinking, which furthermore formulate the framework of the study. This article presents a critical content review of current literature, and an analysis of 276 cases located from the literature on seven factors (Information Logistics, Technology Logistics, Overall Design Logistics, Collaborative Learning, Active Stimulation, Motivation, and Objective-Driven Activities) regarding their influence on the success of social medial supported learning experiences. All seven factors were found to be significant and included in a static predictive model. An in-depth comprehension of this static predictive model is provided, based on which a new dynamic model is proposed.*

Keywords: dynamic learning, dynamic design, dynamic thinking, design logistics, information logistics, technology logistics, social media, influential factors

1. Introduction

Social media is internet-based technology applications that facilitates the sharing of ideas, thoughts, and information through the building of virtual networks and communities (Carroll,Bruno, & vonTschudi,2016; Cetinkaya, 2019; Ehiobuche & Justus, 2016). It provides users prompt digital communication of content, such as text messages, document files, videos or photos (Collins, 2010; Kelm, 2011; Odom, Dunn

& Owen, 2019; Ponnammal, 2016). Users usually engage with social media through computer, tablet or smartphone via web-based software or web applications (Arshad & Akram, 2018; Rosenberg, Terry, Bell, Hiltz, & Russo, 2016; Wiebesiek, 2015). Besides an important means of communication and entertainment, social media have gradually been used in and had an impact on education (Ainin, Naqshbandi, Moghavvemi, & Jaafar, 2015; Halligan, 2010; Ramírez, 2018), and the tools include Facebook (Chugh & Ruhi, 2018; Gorghiu, Pribeanu & Lamanauskas, 2016), Twitter (Forgie, Duff & Ross, 2013; Halpin, 2016; Luo & Xie, 2019), YouTube (Reynolds, Platt, Malone & Foster, 2017; Sweeny, 2009), Instagram (Al-Bahrani & Patel, 2015), Blog (Muñoz & Culton, 2016; Roland, Johnson & Swain, 2011), LinkedIn (Collins, 2010; Lofgren, Shultz & Shea-Porr, 2015), Toolkit (Gülbahar, Rapp, Kilis, & Sitnikova, 2017), Snapchat and a variety of other tools (Forman, 2017).

21st century's learners are featured as a generation of learner-centered and media driven learners (Arquero, del Barrio-García, & Romero-Frías, 2017; Bagarukayo, 2018; Gray, 2018; Heick, 2015). Nowadays, educators have increased their efforts to explore the potential of using the social media tools to enrich learning activities and promote interactive and collaborative learning (Fan & Yost, 2019; Gleason & von Gillern, 2018), at K-12 education levels (Georgakainas & Zaharias, 2016; Martin, Wang, Petty, Wang, & Wilkins, 2018) and higher education levels (Bagarukayo, 2018; Cooke, 2017; Peruta & Shields, 2017). Previous studies have showed the social media's influences on learning processes, communication and collaboration enhancement, and academic performance, regarding learners' personality and learning style (Spackman & Larsen, 2017; Zachos, Paraskevopoulou-Kollia & Anagnostopoulos, 2018), digital thinking (Samuels-Peretz, Camiel, Teeley, & Banerjee, 2017), learners' attitudes (Johnston, Chen, & Hauman, 2013; Khoshnood, Nouhi, & Sabzevari, 2016), anxiety (Ramazanoğlu & Toytok, 2018), motivation (Abulibdeh, 2013; Rosli, Saleh, Aris, Ahmad, Sejzi, & Shamsudin, 2016), and self-directed learning skills (Akgunduz & Akinogl, 2016). Terry Anderson (2019) proposed the challenges to assess the effectiveness and value of social media. Moreover, a critical challenge to educators is that the learning style of our 21st century's learners is characterized as dynamic learning (Liu, Liang, & Li, 2017). Under the context of dynamic learning, how do educators design such a setting to effectively and dynamically integrate certain social media tools to improve learning, and what might be the influential factors that educators need to focus during the design? In literature, we did not find any studies on the design of learning experience to use social media to enhance dynamic learning.

In this article, we employ the concept logistics to explain and redefine *dynamic design* (Liu & Maddux, 2005, 2010), *dynamic learning* (Liu, et al, 2017), and *dynamic thinking* (Ford & Grantham, 2003; Zhang & Zhang, 2013), which furthermore formulate the framework of current study (see the next Literature section). The study focuses on a critical content review of current literature, and an analysis of 276 cases located from the literature on seven factors derived from the literature – *Overall Design Logistics, Information Logistics, Technology Logistics, Collaborative Learning, Active Stimulation, Motivation, and Objective-Driven Activities* (Lee & Liu, 2016; Liu, Li, & Scherer, 2016), regarding their influence on the success of social medial supported learning experiences. The purpose of the study is to examine the influence of the factors and develop a predictive model. This study also provides an in-depth comprehension of how this predictive model can be used in further research and practice, based on which a new dynamic model is proposed.

2. Literature and Background Information

For the purpose of this study, in this literature review section, we first review the concept of *logistics*, and redefine this concept in the context of education. Then, we review and redefine (a) the logistics of dynamic design, dynamic learning, and dynamic thinking, and (b) the logistics of social medial supported learning. Finally we review seven relevant variables including three design-related variables and four learning-related variables.

2.1 The Concept of "Logistics"

Originally, dictionaries define *logistics* as "the branch of military science relating to procuring, maintaining and transporting material, personnel and facilities" (Oxford English Dictionary, 2019), "the detailed coordination of a complex operation involving many people, facilities, or supplies" (New Oxford American Dictionary, 2019), or "the careful organization of a complicated military, business, or other activity so that it happens in a successful and effective way" (Cambridge Dictionary, 2019). *Logistics* was initially a military-based term known as *military logistics*, in reference to how military personnel obtained, stored and moved equipment and supplies to troops in the field (Cloutier & Frank, 2009). The term is now used widely in the business sector, particularly by companies in the manufacturing sectors, to refer to how resources are handled and moved along the supply chain (Bowersox, Closs, & Cooper, 2012). *Business logistics* aims at "having the right item in the right quantity at the right time at the right place for the right price in the right condition to the right customer" (Mallik, 2010, p. 104).

Moreover, logistics has its dynamic dimension. Production logistics can be an example. It describes logistic processes within a value adding system (e.g., a factory or a mine). It aims to ensure that each machine and workstation receives the right product in the right quantity and quality at the right time (Nyhuis & Hans-Peter, 2009). *Production logistics* is dynamic as manufacturing in any plant is a constantly changing process, machines are exchanged and new ones added, which gives the opportunity to improve the production logistics system dynamically.

To this point, we may summarize the definition of logistics *as dynamically coordinating the very basic and operational units, functions, or activities of a system to implement the best performance and produce expected products or outcomes*. When we apply the concept of *logistics*, we start from its three key attributes: (a) specifying the system – it can be the system of military, business, companies, productions, construction, and more (Cloutier & Frank, 2009), or education, teaching, learning and design (applied and discussed in this study); (b) defining the basic and operational units, functions, or activities of the system and how they are divided into; and (c) the way of coordinating dynamically for best performance, which will follow the structure, functions, rules, or purposes of the system. Next, we will discuss *logistics* in the context of education and current study particularly.

2.2. Logistics of Dynamic Design, Dynamic Learning, and Dynamic Thinking

With all the rapidly developed technology tools available for educational practice, *dynamic learning* becomes an evident learning style of the 21st century's learners

(Liu & Gibson, 2018; Sahin, 2009). From the instructor's side, *dynamic design* is the key to produce and deliver effective instructions for students' dynamic learning (Liu, 2017; Liu & Gibson, 2018).

Two types of design, *dynamic* versus *static* design, were proposed early in 2005 by Liu and Maddux that *dynamic design* features as nonlinear, multiple-dimensional, process-based, and open-ended design, while *static design* is linear, single-dimensional, state-based, and closed-ended design (Liu & Maddux, 2005). Both were examined over time, and results constantly confirmed that dynamic design would have more positive impact on learning outcomes (Liu, Li, & Scherer, 2016; Liu, Liang, & Li, 2017; Liu & Maddux, 2010). In early years, the five components of design, known from the ADDIE model – Analysis, Design, Development, Implementation, and Evaluation (Gagne, Wager, Golas, & Keller, 2005), were examined separately as single variables at the completion of learning procedures or events. In recent years, each of the five components was examined as a function of functions with dynamic variables during the learning processes (Liu & Gibson, 2018). Logistics of dynamic design indicates the coordination of all the operational units of dynamic design to achieve the planned objectives.

Dynamic learning occurs when the courses, lessons, learning materials, learning activities, any related learning units or events are designed with either nonlinear, multiple-dimensional, process-based, or open-ended design. Dynamic learning also goes along with dynamic assessment. The most distinguished part of dynamic assessment is that it can be performed at any on-going time point of learning, which would provide the information of both students and the instructor's performance, and hence, allow the instructor to adjust the methods, materials, activities, difficulty levels or pace of learning at any point of learning procedures (Liu, Chen, Han, Kerrigan, Vuthaluru, & Gibson, 2019; Liu, Liang, & Li, 2017). Logistics of dynamic learning describes the coordination and completion of all the learning tasks and activities of dynamic learning that follow the dynamic design principles.

When conducting and implementing dynamic design and dynamic learning, dynamic thinking is always performed (Liu & Gibson, 2018). Originally, dynamic thinking can be defined as "the ability to make optimal decisions in changing environments" (DynamicMinds, 2019; Ford & Grantham, 2003), and the way of thinking that continuously invests in adopting and adapting new habits of mind that allow one to think and respond to challenges critically and creatively (Schoner, 2014; Zhu, 2019). Dynamic thinking often occurs in a dynamically process-based environment (Liu & Gibson, 2018), such as in problem solving (Pelczer, Singer, & Voica, 2009, 2014), mathematics learning (Moreno-Armella, Hegedus, & Kaput, 2008), and tasks required dynamic metacognitive processes (Zhang & Zhang, 2013). In the context of current study, logistics of dynamic thinking attaches to the thinking processes to perform or implement the basic tasks under dynamic design and dynamic learning.

Overall, when educators deliver dynamic learning, actually, they are carrying out a four- dimension (4-D) integration of dynamic design, dynamic learning, dynamic thinking, and dynamic assessment. This integration coordinates and implements sets of tasks and procedures under each of the four dimensions, which can be understood as the logistics of dynamic design, learning, thinking and assessment. The logistics of dynamic learning, including tasks or the basic operational units of learning and the way to coordinate them, may never be the same across individual cases, learning contexts, subject areas, or learners at different levels. Next, we will discuss the context of social media supported learning as an example.

2.3 Logistics of Social Media Supported Learning

Keeping the logistics of dynamic design and learning in mind, we look at the three attributes of logistics, as described above, in the context of social media supported learning. Firstly, we can view the social media supported learning as a system. The function of this system is to deliver learning, which involves learners and instructors, social media uses, design of learning, all related material and activities, assessment, and plans of improvement during the procedures (Liu & Gibson, 2018). The product of the system is the learning outcome.

Secondly, we analyze and list the very basic operational units or tasks of this system. From the instructor's side, the instructor needs to complete the design, that is, to apply the ADDIE model in the design of learning contents and use of social media (Liu & Maddux, 2008; Liu & Velasquezbryant, 2003). For example, some basic units or tasks can be: conducting learner assessment and needs assessment, conducting learning content analysis, setting the goals and objectives of learning, developing materials, locating learning resources, preparing the use of social media tool(s), determining the activity tasks, roles, procedures, and more detailed work based on particular learning context.

From the learners' side, learners need to perform all the required learning tasks or activities. For example, they need to complete learning materials, participate media-based discussions or collaborative projects, raise critical questions, create interactive networks, and provide peer-evaluations (Chen & Liu, 2018, 2019).

During learning procedures, any expected or unexpected issues, problems, events, or even new learning objectives may occur, as the entire procedure is a dynamic procedure with nonlinear, multiple-dimensional, processes-based, and open-ended activities and learning tasks (Liu & Chen, 2018; Liu & Maddux, 2005). This requires the instructor to dynamically involve in the social media based learning along with learners' dynamic performances.

Finally, the core of logistics of social media supported learning is how to coordinate all the basic operational tasks described above to produce the expected learning outcomes. Besides following the theories or design models, instructors may want to change some traditional thoughts about teaching and learning, as this is really an equal involvement procedures from both the learners and the instructor (Ab Rashid, Yahaya, Rahman, & Yunus, 2016; Mnkandla & Minnaar, 2017). Instructors need to involve in the learning activities with students to obtain the first hand dynamic assessment data, along with the ongoing performance data collected from the information platform, so dynamic learning can constantly move to the right direction, and produce expected learning outcomes (Liu & Chen, 2018). The coordinating procedures or methods are exactly the dynamic dimension of the logistics.

Next, we will explore the relevant factors that may influence social media supported learning.

2.4. Relevant Factors

We employ the concept of logistics to describe dynamic design and dynamic learning with the relevant coordinating procedures. Integrating this concept with an

ITD technology based learning model, where Information (contents), Technology (tools), and Design (strategies and methods) formulate a system that applies ADDIE components (Gagne et al, 2005) to produce effective instructions (Liu & Maddux, 2008; Liu & Velasquezbryant, 2003), the following factors are revealed from the literature, including three design-related factors and four learning-related factors.

Overall Design Logistics. Overall design is about the decisions made on overall strategies or methods of learning (Liu, Ripley, & Lee, 2016). Logistics of the overall design is about the procedures or methods to coordinate the necessary changes of the overall strategies that are caused by the expected or unexpected issues during the process of dynamic learning, and to produce successful learning outcomes (Bowersox et al, 2012; Liu & Maddux, 2005). Mostly, overall design logistics is closely related to the information logistics and technology logistics.

Information Logistics. Information is about learning content – all content related hard copy or digital materials, programs, and resources that are used to achieve the learning objectives (Lee & Liu, 2016). Information logistics is to deal with the variation or adjustment of learning contents when nonlinear, multiple-dimensional, process-based, or open-ended dynamic learning occurs (Liu & Maddux, 2005). Again, it is the coordination between the originally planned information and the changed information, and how the adjusted information is delivered (Liu & Gibson, 2018).

Technology Logistics. Technology is about the social media tools, technology equipment or platform needed to use the tools, learners' access to them, available tech-support system, and all technology related components that are necessary to perform social media supported learning (Dini & Liu, 2017). Technology logistics is to coordinate the use of all related technology components to meet the needs of content changes or design changes during social media supported learning (Liu & Gibson, 2018).

The above three factors are design-related factors. Their original versions (overall design, information design, and technology design) are from the ITD model and have been demonstrated to have a significant impact on a variety of technology based learning (Liu, Li, & Scherer, 2016; Liu, Rapley, & Lee, 2016; Liu & Velasquezbryant, 2003). In this study, we integrate the concept of logistics into the original version of the three factors, emphasizing the dynamic feature of the three factors, which is not found in any studies in the literature. Next, we continue to review four learning-related factors.

Collaborative Learning. One purpose of using social media is to conduct collaborative activities. Social media tools allow users to post information, reply to others, and interact with the network (Carroll, Bruno, & vonTschudi, 2016; Cetinkaya, 2019). Studies have found that social media has created a new avenue for communication and collaboration that has a positive impact on learning (Fan & Yost, 2019; Prince, 2004; Seifert, 2016).

Active Stimulation. Active learning is a key in a variety of types of technology based learning (Roach, 2014; Roehl, Reddy, & Shannon, 2013). It features instructional methods that actively engage learning, such as collaborative learning and problem-based learning (Prince, 2004). Social media tools are also seen as a means to stimulate communications and learning involvement, so the factor active stimulation has caught educators' attention (Yavich, Davidovitch, & Frenkel, 2019).

Motivation. Motivation has been found to be a predictor variable that influences computer-based learning (Liu & Jones, 2004; Lee & Liu, 2016), and social media supported learning (Abulibdeh, 2013; Rosli et al, 2016). Especially, intrinsic motivation factors have a direct or indirect impact on technology based learning (Dini & Liu, 2017). We want to see how the factor of motivation is addressed or considered in the studies on social media supported learning.

Objective-Driven Activities. When using social media tool, very often the communications are in a random flow, and very often the conversations have gone to all directions. This brings back a long-time discussed topic, objective-driven learning with objective-driven activities (Wirtz & Tomlin, 2000). When the objectives are clearly regulated, learning seems more likely go toward the expected directions (Mehvar, 2011), even if with dynamic learning procedures.

In summary, from the literature, the three design-related factors (*Overall Design Logistics, Information Logistics, and Technology Logistics*) and the four learning-related factors (*Collaborative Learning, Active stimulation, Motivation, and Objective-Driven Activities*) are of our interest. A critical content analysis in literature on social media supported learning is introduced next, and the seven factors are examined whether or to what extent they could influence the possibility of a social media supported learning case to be successful as described in the literature.

3. Content Analysis and Influential Factors

3.1. Research Questions

The content analysis on the social media supported learning cases was guided by the following research questions:

1. Can the probability that a social media supported learning case is successful be predicted by any of the seven variables — *overall design logistics, information logistics, technology logistics, collaborative learning, active stimulation, motivation, and objective-driven activities?*

2. To what extent do the significant variables (if any from question 1) influence the probability of a social media supported learning case to be successful?

3.2. Priori Power Analysis to Determine the Sample Size

According to the purpose of the content analysis, and the research questions, we conducted a logistic regression for the data analysis. To determine the appropriate sample size for the logistic regression, a priori power analysis was performed.

G*Power 3.1.9.4 was used to estimate the sample size needed for binary logistic regression with independent predictors. In G*Power 3.1.9.4, eight or nine parameters need to be chosen or entered for estimating minimum sample size for logistic regression, depending on the shape of the distribution for the predictor (i.e., X). In this study, eight parameters needed to be determined because all the predictors were binary variables. These eight parameters were (1) one-tailed or two tailed test, (2) odds ratio (effect size), (3) Pr(Y =1|X=1) H0 (i.e., the probability of observing an event given the predictor =1 under null hypothesis), (4) α level, (5) desired statistical power, (6) R2 other X (i.e., the proportion of variance of X explained by additional predictors in the model), (7) the shape of X distribution, and (8) X parm π (i.e., the parameter of X distribution).

We entered the test as a one-tailed test because all the predictors were assumed to enhance learning. For the effect size, we examined previous studies (Catalano, 2015; Xu et al., 2019; Yen & Liu, 2009) and estimated the effect size measured by odds ratio for the predictors to be at least 1.5. We expected that if the null hypothesis is true, the probability of an event (=success) under X=1 is .5. The α level was pre-specified as .05 and we would like to achieve the statistical power of .8. All the predictors were independent from each other and all were binary variables. Because we expected that the instructors were familiar with the learning and design theory, we chose π = .6 for the distribution of the predictor. Therefore, we entered Pr(Y =1|X=1) H0 = .5, α level = .05, statistical power = .8, R2 other X = 0, X distribution = Binomial, and X parm π = .6 in G*Power. We used four values of odds ratio. The resulted minimum sample sizes were 637, 225, 134, and 96 for the odds ratios of 1.5, 2, 2.5, and 3, respectively.

3.3. The Sample of the Cases

The sample of cases were selected from social media supported learning literature from 2014 to 2019. Originally, more than 350 referred journal articles were reviewed including quantitative studies, qualitative studies, and on-going projects. Cases were identified from the articles according to the experiences described by the authors. A case from an article was selected and coded so long as the article provides necessary information for the analysis: the learners, the learning subject, procedures of the social media supported learning experiences, and outcomes from the learners and their experiences.

Finally, 276 social media supported learning cases were selected from the 350 articles for the content analysis. According to the priori power analysis results, if we expect the odds ratio between 2 and 1.5, a minimum sample size between 225 and 637 should be reasonable. Therefore we considered 276 to be a proper sample size for current study.

Among the 276 cases, media tool use ranged from Facebook (30.1%), Twitter (22.8%), Blog (13.4%), Instagram (7.6%), YouTube (7.9%), and other tools such as Text, Message, LinkedIn or ResearchGate (18.1%). Main types of application are teaching (21.4%), learning (44.9%), communications (27.2%), and others such as professional development and administrative use (6.5%). The case participants are teachers (25%), students (55.8%), professionals (10.5%), and others such as administrative faculty and staff (8.7%).

3.4. Factors Examined and Coding

Again, the purpose of the case analysis was to explore the factors or variables that influence the probability of a social media supported learning case to be successful as described in the literature. In this analysis, the response variable was Social Media Supported Learning (SMSL). The SMSL was coded according to the statement made by the author(s) of the case article. For a given case selected from an article, a value of 1 was coded for "success" when the case met any one of the criteria: (a) SMSL resulted in better learning outcomes if the outcomes were quantitatively measureable such as evaluation scores, (b) SMSL exhibited expected features in student learning performance if the outcomes were summarized from observations or qualitative data, or (c) SMSL showed positive trends in learning performance towards improved learning outcomes if the case was an on-going study. Otherwise, a value of zero was coded for an "unsuccessful" case. The seven factors summarized from the literature were explanatory variables (or predictor variables). They were coded as in the following.

For the three design related factors, *Overall Design Logistics* (ODL), *Information Logistics* (IL), *Technology Logistics* (TL), they were coded as 1 for a given case, when these dynamic logistics features were met: (a) the basic operational tasks or activities for either overall design, information, or technology logistics were specified, and with any of the dynamic design criterion (that is, to either operate non-linearly, at multiple dimensions, through process-focused procedures, or with open-ended directions), and (b) the way how they were dynamically coordinated, based on relevant theories or models, were clearly explained in the article from which the case was selected. Otherwise, a value of zero was given to code the variables as “dynamic logistic not presented” for the case.

The other four learning related factors were: *Collaborative Learning* (CL), *Active Stimulation* (AS), *Motivation* (MO), and *Objective-Driven Activities* (ODA). They were coded as 1 for a given case, if the article provides detailed descriptions of the strategies, methods, activities, or models used to establish a collaborative learning environment, to actively stimulate or motivate student learning, and to provide objective-driven guidance for learning in the social media supported learning case. A value of zero was given for the absence of the features in a variable. Table 1 shows the coding values for the variables.

3.5. Data Analysis and Results

Logistic regression analyses were conducted using SPSS (version 26) to determine whether *Overall Design Logistics*

Table 1. Variable Coding

Variables	**Values**	
(presented in articles)	1	0
(SMSL) – Social Media Supported Learning (RV)	Successful	Unsuccessful
(ODL) – Overall Design Logistics (EV)	Dynamic	Static
(IL) – Information Logistics (EV)	Dynamic	Static
(TL) – Technology Logistics (EV)	Dynamic	Static
(CL) – Collaborative Learning (EV)	Yes	No
(AS) – Active Stimulation (EV)	Yes	No
(MO) – Motivation (EV)	Yes	No
(ODA) – Objective-Driven Activities (EV)	Yes	No

Note: RV—Response Variable, EV—Explanatory Variable

(ODL), *Information Logistics* (IL), *Technology Logistics* (TL), *Collaborative Learning* (CL), *Active Stimulation* (AS), *Motivation* (MO), and *Objective-Driven Activities* (ODA) could be used to predict the success of a *Social Media Supported Learning* (SMSL) Case. The assumptions of logistic regression were checked and no violations were found. Frequencies for each variable are shown in Table 2.

Results from the logistic regression showed that the model with these seven explanatory variables was significant ($\chi^2 = 121.724$, $p < .001$) and accounted for about 49.8% of the variation in the response variable (Nagelkerke $R^2 = .498$), indicating that this model significantly predicts group membership. The Hosmer and Lemeshow Goodness-of-Fit Statistic of 6.624 ($p = .578$) was not significant, indicating that the hypothesis that the model provides a good fit of data should be accepted. Specifically, 59 out of 89 unsuccessful cases (66.3%), 171 out of 187 successful cases (91.4%), and a total of 230 out of 276 cases (83.3%) were correctly predicted by the model.

Table 2. Frequencies

Variables	**Values**	
(presented in articles)	1	0
(SMSL) – Social Media Supported Learning (RV)	187	89
(ODL) – Overall Design Logistics (EV)	193	83
(IL) – Information Logistics (EV)	152	124
(TL) – Technology Logistics (EV)	169	107
(CL) – Collaborative Learning (EV)	143	133
(AS) – Active Stimulation (EV)	163	113
(MO) – Motivation (EV)	142	134
(ODA) – Objective-Driven Activities (EV)	176	100

Note: RV—Response Variable, EV—Explanatory Variable

A significant Wald chi-square value for a given variable indicates that the variable is significantly related to the response variable. As shown in Table 3, the Wald chi-square values are significant for all seven explanatory variables. Therefore, all seven explanatory variables are included in the model equation. The Parameter Estimate generates the

Table 3. Logistic Regression Outputs

Predictors	DF	Parameter Estimate	Standard Error	Wald Chi-Square	P	Odds Ratio
(IL)	1	1.369	0.363	14.245	.001	3.933
(TL)	1	0.933	0.343	7.394	.007	2.542
(ODL)	1	1.407	0.353	15.843	.001	4.083
(CL)	1	0.675	0.340	3.944	.047	1.965
(AS)	1	1.070	0.337	10.087	.001	2.917
(MO)	1	1.170	0.348	11.286	.001	3.222
(ODA)	1	1.089	0.368	8.764	.003	2.970
Constant	1	-3.407	0.511	44.487	.001	0.033

Response variable: Social Media Supported Learning (SMSL)
Explanatory variables: Information Logistics (IL), Technology Logistics (TL), Overall Design Logistics (ODL), Collaborative Learning (CL), Active Stimulation (AS), Motivation (MO), and Objective-Driven Activities (ODA)

estimated coefficients of the fitted logistic regression model, and they are used to formulate the following logistic regression equation (1):

$$\begin{aligned} \text{logit}\,(\hat{p}) = -3.407 &+ 1.369(IL) + 0.933(TL) \\ &+ 1.407(ODL) + 0.675(CL) \\ &+ 1.070(AS) + 1.170(MO) \\ &+ 1.089(ODA) \text{ ---------------(1)} \end{aligned}$$

The sign (ˆp) indicates an estimated probability value for the response variable SMSL to be 1. The logit (ˆp) called log odds, and logit represents logit transformation of the event probability.

An estimated coefficient indicates the contribution that particular explanatory variable makes to the possibility of the response variable being 1.For example, when the variable CL changes from 0 to 1 (that is, when collaborative learning strategies or activities are applied in the social media supported learning experience) with all other predictors fixed, the logit transformation of event probability (that the social media supported learning case to be successful as described in the literature) increases by 0.675 (see Table 3). The estimated coefficients for the other six explanatory variables can be interpreted similarly.

Odds ratio is another statistic to explain the contribution of an explanatory variable to the model. If the odds ratio for a given explanatory variable is larger than 1, the probability of the response variable being

1 increases because of the presence of that explanatory variable. For example, the odds ratio for variable CL (*Collaborative Learning*) is 1.965 (see Table 3), indicating that a social media supported learning case would be 1.965 times more likely to be successful if collaborative learning is engaged in the case, compared to cases that do not engage collaborative learning. If the odds ratio is smaller than 1, the probability of the response variable being 1 decreases (that is, the probability of a social media supported learning case to be successful decreases when that explanatory variable exists). As seen in Table 3, all seven odds ratio values are larger than 1 (ranged from 1.965 to 4.083), therefore, all seven variables positively contribute to the success of a social media supported learning case.

3.6. Summary of the Case Analysis

In summary, all the three design-related variables (*Information Logistics, Technology Logistics, and Overall Design Logistics*) and four learning-related variables (*Collaborative Learning, Active Stimulation, Motivation, and Objective-Driven Activities*) significantly contribute to the model, and positively influence the success of a social media supported learning (SMSL) case. That is, the probability of a SMSL case to be successful increases when (a) the dynamic logistics features for the three design-related variables are met, and (b) collaborative learning environment, active stimulation or motivation to learning, and objective-driven guidance for learning are provided. Next we present an in-depth explanation of the model and how it can be used in our research and practice.

4. Comprehensions of the Model for Research and Practice

Addressing back to the purpose and research questions of the case analysis, this section includes (a) a static prediction model function developed from the current study, (b) the specific attributes of the static prediction model, and (c) a new proposed dynamic prediction model for research and practice.

4.1. The Static Predictive Model Function

According to the results from the logistics regression and the relationships between the seven explanatory variables and the response variable, a predictive model can be

P (SMSL=1) = *f* [IL, TL, ODL, CL, AS, MO, ODA] --------------------------------- (2)

Where:

SMSL = Social Media Supported Learning **P (SMSL=1)** = *Probability of SMSL to be successful*

***f* […]** indicates "a function of …"

IL = Information Logistics, **TL** = Technology Logistics, **ODL** = Overall Design Logistics,

CL = Collaborative Learning, **AS** = Active Stimulation, **MO** = Motivation,

ODA = Objective-Driven Activities

Figure 1. Static predictive model function

summarized into the following model function equation (2) in Figure 1.

Model function (2) reads "the probability of a SMSL case to be successful is a function of information logistics, technology logistics, overall design logistics, collaborative learning, active stimulation, motivation, and objective-driven activities." It exhibits the relations between the group of explanatory variables and the response variable. Logistic regression equation (1) in the "Data Analysis and Results" section is the concrete model that describes all specific predictive relations or influences. This model function (2) basically is a conceptual model.

At this point, we still define this model as a static model, as we treat each of the seven explanatory variables as a single variable, and the success of a SMSL is a function of the combination of the seven single variables, where each variable has a single value of 1 or 0.

4.2. The Attributes of the Static Predictive Model

As described above in the "Data Analysis and Results" section, odds ratio can be used to explain the contribution of an explanatory variable to the model. For example, the odds ratio for variable Motivation is 3.222 (see Table 3), indicating that a social media supported learning case would be 3.222 times more likely to be successful if activities to motivate the learners is engaged in the case, compared to cases that motivation activities are not engaged. Furthermore, what is the contribution of the variable(s) regarding to the probability of a case to be successful?

For any given case, the logistic regression equation (1) can be first used to calculate the log odds, which then can be converted into the probability of the SMSL case to be successful, P(SMSL=1). For example, when all seven predictor variables are included in a case (each is coded as 1), the following steps can be performed to calculate such probability:

1. Calculating the log odds with equation (1):

$$\begin{aligned}\text{log odds} &= -3.407 + 1.369*1 + 0.933*1 \\ &\quad + 1.407*1 + 0.675*1 + 1.070*1 \\ &\quad + 1.170*1 + 1.089*1 \\ &= 4.306\end{aligned}$$

2. Calculating odds: odds = exp (4.306) = 74.143 (exp stands for *exponential function*)

3. Converting odds to probability: P(SMSL=1) = 74.143 / (1 + 74.143) = 0.986

That is, when all seven explanatory variables are considered in the case, the probability of a SMSL case to be successful is .99. Next, we can compare the calculated probabilities with different combinations of the variables.

Three Design-Related Variables. The three design-related variables, *Information Logistics* (IL), *Technology Logistics* (TL), and *Overall Design Logistics* (ODL) are the foundation of the SMSL model. They represent the features of dynamic design and dynamic learning, specify the basic operational tasks or activities of overall design, information, or technology logistics that meet with dynamic design criterion, and the way to dynamically coordinate all the activities. If an SMSL case only includes these three variables, according to the logistics regression model, the probability of the case to be successful is .574 with the same calculations:

1. Calculating the log odds with equation (1):

$$\text{log odds} = -3.407 + 1.369*1 + 0.933*1 + 1.407*1 + 0.675*0 + 1.070*0 + 1.170*0 + 1.089*0$$

$$= 0.302$$

2. Calculating odds: odds = exp (0.302) = 1.352 (exp stands for exponential function)

3. Converting odds to probability: P(SMSL=1) = 1.352 / (1 + 1.352) = 0.574

Compared the probability calculated from this three-variable base model (.57) with that of the full model (.98), we can tell the difference, and conclude that adding one or more of learning-related variables to the model may increase the probability of an SMSL case to be successful.

Three Design-Related Variables and One Learning-Related Variable. Using the same calculation procedures, the probability of an SMSL case to be successful, P(SMSL=1), calculated with models that include the three design-related variables and one more learning-related variable are:

- P (SMSL=1) = .72, with the model that includes the three design-related variables and *Collaborative Learning.*
- P (SMSL=1) = .79, with the model that includes the three design-related variables and *Active Stimulation*.
- P (SMSL=1) = .81, with the model that includes the three design-related variables and *Motivation*.
- P (SMSL=1) = .80, with the model that includes the three design-related variables and *Objective-Driven Activities*.

Again, compared the probability calculated from the three-variable base model (.57), the contribution of each learning-related variable to the prediction model is clearly demonstrated. Similarly, the probability increases when adding two or three more learning-related variables to the three-variable base model, for example,

- P (SMSL=1) = .88, with the model that includes the three design-related variables, and *Collaborative Learning and Objective- Driven Activities*.
- P (SMSL=1) = .97, with the model that includes the three design-related variables, *Active Stimulation, Motivation, and Objective-Driven Activities*.

Comparing the calculated probabilities from models with different combinations of the variables provides in-depth comprehensions of the model. In a SMSL case, different attributes or components may apply to each of the variables, and have different or a new combined impact on the learning outcomes, which initiates our thoughts to propose the following dynamic predictive model.

4.3. A New Proposed Dynamic Predictive Model

The predictive model in Figure 1 is a static model, as we treat each of the seven explanatory variables as a single variable, and the success of a SMSL is a function of the combination of the seven single variables, where each variable has a single value of 1 or 0. With the idea of dynamic design, if we measure each of the variables from multiple dimensions, with dynamic data in a developmental approach, each of the seven variables can be a function of a set of other relevant variables. For example, in the static model, *Information Logistics* is a variable indicating the existence or absence of the components such as the design of content information, a set of basic learning units and tasks, and the features of how they are coordinated into the learning experiences. It is coded as 1 or 0. However, if we have an assessment system to measure each of the components under the variable, *Information Logistics* will become a function of all the measurements on those components. To think dynamically and treat each of the variables in the static model as a function of a set of other relevant variables, the original static prediction model will become a dynamic model, indicating the function of functions as

$$\mathbf{P\ (SMSL{=}1) = F\{\mathit{f(IL), f(TL), f(ODL), f(CL), f(AS), f(MO), f(ODA), f(T)}\}} \text{ --------- } (3)$$

Where:

SMSL = Social Media Supported Learning **P (SMSL=1)** = *Probability of SMSL to be successful*

f(…) indicates "a function of …" **F {…}** indicates "the function of ***functions***"

IL = Information Logistics, **TL** = Technology Logistics, **ODL** = Overall Design Logistics,

CL = Collaborative Learning, **AS** = Active Stimulation, **MO** = Motivation,

ODA = Objective-Driven Activities, **T** = Time

Figure 2. Dynamic predictive model function

expressed in Figure 2, with model function equation (3).

Model function (3) reads "the probability of a SMSL case to be successful is the *function of a set of sub-functions*, including the functions of *information logistics, technology logistics, overall design logistics, collaborative learning, active stimulation, motivation, objective-driven activities, and Time.*"

Notice that, in the dynamic model function (3), we added a sub-function of time *f(T)*. The core idea of this dynamic model is to predict, which involves motion and the time to make the motion. We can view the dynamic model as a dynamic system. "Thinking of a single variable, it characterizes the state of a system" (Schoner, Spencer, & DFT, 2016, p. 13). While a dynamic system focuses on the procedure of motion, instead of any single variable, we need a set of sub-functions to formulate the motion or the dynamic changes, with a function of Time, to achieve the prediction.

With this dynamic model, a variety of variables under each of the seven sub-functions can be explored or studied, and such studies would provide multiple-dimensional framework and logistics for us to design and examine dynamic learning.

5.Discussion and Conclusions

In summary, we have reviewed the literature in social medial supported learning, and performed a critical content analysis on 276 cases, from which a static predictive model was generated with seven variables that positively influence the success of a social medial supported learning case. We also provided an in-depth comprehension of the static predictive model, based on which a new dynamic prediction model was proposed for further research and practice.

We have reached the following conclusions: (a) logistics leads to dynamic thinking, (b) dynamic thinking can be facilitated with SMSL for both learners and instructors, (c) logistics is measurable in the settings of dynamic learning, and (d) the effect size of this study is consistent with that from similar studies in the literature.

5.1 Logistics Leads to Dynamic Thinking

To make an argument, the promises are as follows. First, we imported the concept of logistics into the context of education, and particularly in this study defined the variables of *Information Logistics, Technology Logistics, and Overall Design Logistics*. The three attributes are the system, the basic and operational units or tasks of the system, and the way to coordinate among the units for best performance and achieve the goals of the system.

Second, learning can be thought as such a system, when all the basic and operational units or tasks are performed dynamically, that is, nonlinearly, at multiple-dimensions, with process-based activities, to reach open-ended outcomes (Liu & Maddux, 2005), the system dynamically coordinates all these dynamic units to achieve the learning goals. This is what *Dynamic Learning* is about.

Finally, dynamic thinking is necessary to dynamic learning (Liu & Gibson, 2018). It is the process of thinking that deals with continually changing situations or tasks (Schoner, 2014; Zhu, 2019), and the logistics of dynamic thinking attaches to the thinking processes to perform or implement the basic tasks under dynamic learning.

From the above promises, we can see that logistics is the main line that runs through the reasoning. So, we can conclude that *logistics leads to dynamic thinking*. Dynamic thinking is not any independent process, it always attaches to concrete tasks in a process-based environment, to deal with changes, to solve problems that are constantly generated in our learning. The key point is to find out the very basic units and work them out. The conceptual framework of logistics can help through the thinking and problem solving.

5.2 Facilitate Dynamic Thinking with SMSL

The second conclusion from this study is that *dynamic thinking can be facilitated with social medial supported learning experiences for both learners and instructors*.

This study finds that the probability of a SMSL case to be successful increases when dynamic design principles are applied into *the Information Logistics, Technology Logistics,* and *Overall Design Logistics*. When using social media tools for communications or learning, the learning path may not be linear because: (a) the information processed with social media tools can be very diverse, (b) the problems occurred can be at different levels, and hence (c) the process-based learning can be at different directions or pace, which all may lead to the open-ended outcomes. This open-ended outcomes will be the initial point of next step of learning.

Learners in such a dynamic SMSL environment will naturally perform dynamic thinking to certain extent. This does highly require the instructor's skills of dynamic thinking to (a) deal with the dynamics of learning procedures, and short term or long term learning objectives and goals, and (b) determine the extent to which the instructor involves in learners' activities. One challenge for the instructor is to make optimal decisions in such a dynamic learning environment (DynamicMinds, 2019; Ford & Grantham, 2003), and to direct the learning or wrap up the diverse outcomes towards the learning objectives and goals.

5.3 Is "Logistics" Measureable?

Logistics is not a stand-alone variable. It attaches to a certain context or system, basic units in the system, and the way to coordinate all the units. In current study, we used three logistics variables: *Information Logistics, Technology Logistics,* and *Overall Design Logistics*. Each of them was measured and coded as a categorical variable, according whether it met the dynamic design principles.

But, can the three design-related variables be measured quantitatively? For example, in the context of social media supported dynamic learning, when looking into the detailed attributes of each variable, we may need to think: (a) what are the basic units of learning? (b) can the learning outcomes from each units be measureable? what are the scales of the measurements? (c) is the social media tool appropriate for the purpose of learning? (d) how do the learners feel about the media tool and what is their preference? (e) does the instructor use the appropriate strategies to organize and deliver the instructions? (f) what are the strategies to manage expected and unexpected issues or problems in the dynamic learning environment? (g) what are the backup preparations, including learning materials, technology tools that provide equivalent functions, technique support, or time management? to what extent do the backup preparations work effectively in the dynamic learning environment?

All the considerations, as an example, can be turned into certain measurements, which would be the measurements of the *Information Logistics, Technology Logistics,* or *Overall Design Logistics*. This leads to our third conclusion that *logistics is measureable in the settings of dynamic learning*. Although developing instruments to measure all the performances is not a simple job, and the validation and testing of the instruments may take years, we need to think of all the details when designing and delivering instructions.

5.4 The Effect Size

In a logistics regression analysis, odds ratio is an effect size statistic to explain the contribution of a predictor to the model. In this study, odds ratios of the seven predictors ranged from 1.965 to 4.083 (see Table 3), indicating their positive influence on the probability of a SMSL case to be successful.

The range of effect size from similar studies in the literature can provide a general reference to our study – to what extent the findings from our study is consistent with the literature. Yen and Liu (2009) examined the relation between scores on students' learner autonomy and course success. Their findings showed that the odds ratio of course success for a person with an X learner autonomy score to a person with an (X–1) learner autonomy score was 1.016. Catalano (2015) investigated the effect of a situated learning environment for knowledge transfer in a distance education information literacy course. University students were randomly assigned to a situated learning condition or a traditional instruction condition. Findings from Catalano (2015) showed that the odds ratio of transfer for a student in the situated learning environment to a student in the traditional instruction condition was 2.9. Xu et al. (2019) studied the effect of teacher factors, individual factors, and course management factors on student's perception of teaching effectiveness. Their findings showed that teacher's knowledge level, heuristic teaching, times of preview literature, and student's study attitudes were significant predictors of teaching effectiveness. The odds ratios of the seven predictors in the logistic model ranged from 0.02 to 49.673 (Xu et al., 2019).

In conclusion, *the odds ratios of the seven predictors in our study (ranged from 1.965 to 4.083) were consistent with those from the literature.*

5.5. Limitations and Further Studies

One limitation of this study is that the static model was generated with the data coded from the literature, purely based on the descriptions in the articles. This is a disadvantage of content analysis, as in some articles, it is difficult to explore the experimental conditions or case settings in-depth. The seven predictor variables are clearly presented in some cases, but are ambiguous in some other cases. The studies described in the literature may or may not be duplicable. This points to a fact that the model can only provide a macro framework as initial steps for further practice and studies. More solid work needs to continue.

The static predictive model, although it is based on social media supported learning literature, can still be applied in a general education setting. It is the authors' hope that findings from this article, and the dynamic predictive model as well, could provide useful reference to other educators and researchers, and generate more research ideas. Further studies could be conducted (a) to examine the validity and reliability of both models with larger size of first hand data, (b) to examine the effectiveness of using this model on student learning with experimental design, or (c) to explore more relevant factors and revise these models. We welcome any comments and suggestions.

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