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Influential Factors on Technology-Based Learning in Science, Mathematics, and Engineering (SME): A Case-Analysis from 305 Studies

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With new technology tools available for educators and students, effectively using these tools to improve teaching and learning has become a constant theme for research and practice in the field of education. In this study, case-analysis was conducted on 305 published studies (from 140 peer-reviewed regional, national and international journals) that explored the effect of using technology on student learning in science, mathematics, and engineering (SME) at K-12 and university levels. Seven factors were summarized (*Content Design, Technology Design, Integration Design, Interactive Learning, Motivation, New Trends in Content,* and *New Trends in Technology)* and used to generate a logistic predictive model. The model suggests that five of the seven factors significantly predicting the probability of a technology-based SME learning experience to be successful. A technology integration model was tested with the case analysis. Static and dynamic instructional design models and new trends in e-learning are also discussed.

Keywords: science/mathematics/engineering learning, technology integration, design, prediction, interactive learning, motivation, trends in immersive technology

INTRODUCTION

With the rapid development of technology, more and more technology tools are available in the field of education, and have been used to enhance student learning in science, mathematics, and engineering (Becker & Park, 2011; Jeong et al., 2019; Li & Ma, 2010), at K-12 levels (Hew & Tan, 2016; Means et al., 2021; Scott-Parker & Barone-Nugent, 2019) and university levels (Sampaio & Henriques, 2020; Shirey, 2018). Over

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years, researchers have been exploring the effectiveness or successful use of technology in science, mathematics and engineering (SME) learning (Becker & Park, 2011). Most studies examined the fundamental design principles such as the three-dimension technology integration model proposed by Liu and Velasquez-Bryant (2003), and the five-stage instructional design model initiated by Schlegel (1995). Recent studies also assume the new trends in e-learning and technology (Walker, 2021). Research findings suggest effective methods, strategies, learning environments, and some specific intrinsic and extrinsic influential factors that would lead to positive or expected learning outcomes in technology-based SME learning (Ahn, 2019; Cai et al., 2020; Chao et al., 2016; Dickerson & Kubasko, 2007; Yang, 2017).

The purposes of this study were to (a) identify influential factors to technology-based SME learning from published studies, using the instructional design and technology integration models as a framework; and (b) examine to what extent the factors can predict successful technology-based SME learning, using case analysis method. Cases used in this analysis were 305 published studies located from 140 peer-reviewed regional, national and international academic journals. The studies reported experiences of using technology for student learning in science, mathematics, or engineering, from K-12 to university levels.

In the next sections, we present (a) the literature review of the theoretical framework for the study, (b) the methods and procedures of the case analysis, (c) the results, findings, and the predictive model from the case analysis, and (d) the implications to educators' practice, and the suggested directions for future research.

LITERATURE REVIEW

The literature review in this section focuses on: (a) research findings and educational practice in technology-based SME learning, (b) theoretical framework of technology integration design and fundamental instructional design, (c) new trends in e-learning and technology, and (d) relevant factors.

TECHNOLOGY IN SME LEARNING: WHAT WORKS?

In the literature, most studies reported the effectiveness or predictors of technology-based SME learning (Campbell & Abd-Hamid, 2013; Hew & Tan, 2016; Schulze & van Heerden, 2015), and some very thoroughly summarized meta-analysis results also provided the trends, best practice, and critical issues over time (Becker & Park, 2011; Jeong et al., 2019; Li & Ma, 2010; Siregar et al. 2020). Li and Ma (2010) conducted a meta-analysis to explore the effectiveness of using computer technology on K-12 students' mathematics achievements. The analysis involved 36,793 learners from 46 primary studies over 16 years from 1990 to 2006. A total of 85 independent effect sizes were extracted to examine the effect. *Methods of teaching* was one of the strong predictors of the effect of technology on mathematics achievements, where the constructivist approach and traditional approach exhibited different effects on mathematics achievements. More interestingly, *type of technology* was not significant and all types of technology examined in the studies demonstrated the same effects on mathematics achievement. Unfortunately, instructional design was not mentioned at all.

In contrast, another meta-analysis conducted by Jeong et al. (2019) found different results. This study examined the effect of computer-supported collaborative learning (CSCL) in STEM. The authors analyzed 316 outcomes from 143 studies over nine years from 2005 to 2014. Different from Li and Ma's study (2010), Jeong et al. found that the effects of both *technology type* and *pedagogies* were significant. First, the differences across technology types on the CSCL effect is significant, ($Q(17) = 46.18$, $p = .001$) when using certain combinations of technology tools, such as video conferencing and shared workspace (with an effect size of Hedges' g = 0.78), discussion board and information resources (g = 0.48) and chat and representation tools (g = 0.35). Second, the effects of CSCL varied significantly as a function of pedagogies in which they were embedded ($Q(18)$ =29.74, p = .040). For example, CSCL produced a larger effect in the contexts of traditional pedagogy (g =1.01), followed by scaffolding (g = 0.64), and a negative effect with case-based pedagogy (g = -0.19). However, instructional design for different types of technology tool and different context of pedagogies was not mentioned either.

Furthermore, in Hew and Tan's study (2016), learning content design and technology integration design gained more attention. They examined the predictors of technology integration with the data of 32,256 students from 2,519 secondary schools in 16 developed countries. The effect of *IT expectations in curriculum* (the design of learning contents) and *level of IT integration* remained significant. The integration of new technology such as robotics, virtual reality, augmented reality, or mixed reality into SME learning were studied more and in depth recently (Kukreti & Broering, 2019; Sullivan & Bers, 2019; Yannier et al., 2020), and the findings also navigated to a high demand on instructional design and the design of technology integration.

INTEGRATION DESIGN AND INSTRUCTIONAL DESIGN: WHAT IS TRUE?

Theoretical framework for current study consists of a three-dimension technology integration model and a fundamental instructional design model. Liu and Velasquez-Bryant (2003) proposed the ITD three-dimension model, where **I** stands for **I**nformation or learning contents, **T** stands for **T**echnology tools used in learning, and **D** stands for the instructional **D**esign principles. The key point is that any successful technology-based learning requires the integration of all three dimensions, without missing any single dimension. In other words, the ITD model proposes that instructional design principles should be used in the design of information (learning contents), the design of technology use to best fits the learning goals, and the design of technology integration into the activities of teaching and learning to achieve the expected learning outcomes.

The *design* in the ITD model follows the principles and the five stages of a well-applied fundamental instructional design model – ADDIE model. This model was first introduced by Schlegel (1995) as an evaluation instrument for military training, and then promoted into the field of education by Gagné et al. (2005) to guide research and practice in instructional design. The abbreviation ADDIE describes the five stages of instructional design: **A**nalysis, **D**esign, **D**evelopment, **I**mplementation, and **E**valuation. Tasks in the *Analysis* stage include needs assessment, learner assessment, cost/resource analysis, content analysis, setting learning goals/objectives and learning outcomes. At the stage of *Design*, all the operations to achieve the goals and objectives are defined, timeline and personnel are set to execute the to-do list. Following the to-do list, the learning-instructional unit is completed in the *Development* stage, which can be a lesson, an activity, a course, or a program). At the *Implementation* stage, the learning-instructional unit is delivered to the learners. The outcomes are to be evaluated at the stage of *Evaluation* based on the goals/objectives set in the *Analysis* stage at the beginning. Any issues or problems found from the evaluation would be considered in the next round of redesign (Cheung, 2016; Gagné et al., 2005; Nichols-Hess & Greer, 2016; Schlegel, 1995).

With ADDIE integrated in all three dimensions, the ITD model has been tested to be effective over years from a series of case analysis, for example, on the following themes: (a) *using Web 2.0 in teacher education* with 88 published cases (Liu & Maddux, 2008), (b) *the effectiveness of flipped learning* with 216 published cases (Liu, Ripley, & Lee, 2016), (c) *technology and dynamic design in counseling education and practice* with 261 published cases (Liu, Li, & Shcherer, 2016), and (d) *social media in dynamic learning* with 276 cases (Liu, Chen, & Li, 2019). Those case analyses were performed with logistic regressions, and the results consistently demonstrated that *all three dimensions integrated together* was the necessary and sufficient condition leading to the expected learning outcomes. Table 1 shows the model effect size (R^2), significant predictors (or influential factors) in the predictive model of each study, and the minimum and maximum odd ratios (the effect size) for the predictors. Those influential factors are reviewed in more depth in the section *Relative Factors* below.

Table 1. *Case Analyses in the Literature*

Themes	**Case Analysis**	**Model *Nagelkerke* R^2**	**Sig. Predictors**	**Odd Ratios Min. ~ Max.**	**References**
Using Web 2.0 in teacher education	88 cases	.66	• Info design • Tech design (with integration design)	12.09~21.07	Liu & Maddux (2008)
Effectiveness of flipped learning	216 cases	.26	• Content design • Tech design • Overall design • Active learning • Motivation	2.166~2.497	Liu, Ripley, & Lee (2016)
Technology in counseling education and practice	261 cases	.25	• Counseling design • Tech design • Overall design	2.286~2.741	Liu, Li, & Shcherer (2016)
Social media in dynamic learning	276 cases	.49	• Info logistics • Tech logistics • Overall design logistics • Collaborative learning • Active stimulation • Motivation • Objective-driven activities	1.965~4.083	Liu, Chen, & Li (2019)

In the current study, the design models are tested again with 305 cases on the influence of using technology on students' SME learning. The ITD integration model and ADDIE instructional procedures together formulate the theoretical framework that originates the design related factors for the case analysis. Factors related to new trends of e-learning are reviewed in the next section, which will suggest new dimensions of design and learning.

NEW TRENDS IN E-LEARNING AND TECHNOLOGY

On one hand, the fundamental design theories remain in effect to guide the design of instructions and learning from the perspective of the instructor (Nichols-Hess & Greer, 2016). On the other hand, new trends in e-learning and technology have also constantly revealed new challenges to educators and learners, which focus more on new approaches of learning from the perspective of learners (Kumar, 2020; Rienties & Toetenel, 2016). Four types of new trends in e-learning that have been highly advocated can be summarized as: (a) trends in well-practiced technology based learning with more innovative and integrative applications, (b) trends in the context of learning, (c) trends in immersive technology and (d) trends in learning content (Kumar, 2020; ViewSonic, 2020; Walker, 2021). The specific trends under each type are presented in Table 2, and the definitions could be found in the cited references.

Integrative Approach to the Trends. Most studies that adopt or reflect certain new trends in e-learning share a typical common feature that more than one trends are integrated into learning to produce expected learning outcomes. For example, Chen et al.'s (2021) study demonstrated a trend in well-practiced technology-based learning (*video-based learning*) and a trend in content (*microlearning*). *Video-based learning* started from video-based lectures and has come a long way to instructional videos today (Walker, 2021), and *microlearning* is learning content delivered in focused and basic units of about three to five minutes (Park & Kim, 2018). In Chen et al.'s study, they created 12 short instructional videos (or video segments) for 10th graders to learn Right Triangle Trigonometry. The video contents covered the concepts, rules, calculations, practice, problem solving, and collaborative activities. The length of the instructional videos varied from 2 minutes 17 seconds to 7 minutes 43 seconds with a total of 40 minutes 45 seconds. The average length of the videos was about 3 minutes and 20 seconds. Positive results supported the effective use of the *microlearning* contents from the short videos (Chen et al., 2021).

Table 2. *New Trends in E-Learning and Technology*

Types of New Trends	**Specific Trends**
Well-practiced technology-based learning with more innovative and integrative applications	• Video-based learning • Game-based learning/gamification • Mobile learning
Trends in the context of learning	• Adaptive learning • Social learning • Big-data driven (learning analytics)
Trend in immersive technology	• Artificial intelligence (AI) • Virtual reality (VR) • Augmented reality (AR) • Mixed reality (MR) • Robotics (Ro)
Trend in learning content	• Microlearning • Content curation • User generated content (personalized content)

(Summarized from: Kumar, 2020; ViewSonic, 2020; Walker, 2021)

Another study by Dini and Liu (2017a) reflected four trends of e-learning: a trend in immersive technology (*Augmented Reality – AR*), a trend in content (*user-generated content*), and two trends in well-practiced technology-based learning (*video-based learning* and *mobile learning*). AR environments use a video input device to overlay an image over a section of the real world that is viewed through a camera on the device, and the AR image appears to be a part of the real world (video) when the viewer looks at the screen (Dini & Liu, 2017a; Jee et al., 2014). In Dini and Liu's study, 8th graders created their AR storybooks on selected topics of their interests, which illustrated a good example of user-generated content for learning. They then used mobile device to perform required interactive learning activities. Results showed that the AR storybook projects motivated students learning and hands-on activities. Students also developed and improved the skills of communication and collaboration through the project (Dini & Liu, 2017a).

More examples of integrative approach of the trends can be found in literature. In another study conducted by Dini and Liu (2017b), middle school students learned photography skills via *game-based learning* with *mobile learning*, and created their individual photography learning projects that illustrated their work of *content curation* (critical selection and organization of existing pictures) and *user-generated contents* (the pictures they took on the selected themes). Studies also explored the impact of *adaptive learning* on the use of an automated grading system to improve overall learning and effectiveness (Forsyth et al., 2016), and the impact of using *adaptive learning* technology (an adaptive learning system that examines accuracy and response time) to assess learning (Mettler et al., 2011). Furthermore, studies explored the use of *VR*, *AR*, *MR*, and *AI* system (Meyer et al., 2019; Yannier et al., 2020), robotics (Ntemngwa & Oliver, 2018; Sullivan & Bers, 2019), mobile and computer games (Bursztyn et al., 2015; Yasin et al., 2018), and *learning analytics* (Alhadad, 2018; Joksimović et al., 2014; Méndez et al., 2014; Vieira et al., 2016). All studies suggested the methods, strategies, procedures, or conditions of a learning environment that would lead to positive and expected outcomes.

The purpose of reviewing the new trends in e-learning is to explore, in current literature, whether or to what extent any of those new trends are reflected in technology-based SME learning and have associated with the learning outcome. Consistent with the purpose of current case-analysis study, what factors could be formulated from the new trends and examined with the 305 cases?

RELEVANT FACTORS

The literature review reveals seven factors for this study: three design related factors (*Content Design*, *Technology Design*, and *Integration Design*), two new trend oriented factors (*New Trend in Content* and *New Trend in Technology*), and two learning related factors (*Interactive Learning* and *Motivation*). Design related factors are based on the principles of ITD integration model and ADDIE instructional design model as examined in previous case analysis studies (see Table 1). New trend orientated factors are based on the review of new trends in e-learning and technology (see Table 2). Learning related factors are the significant factors for SME learning in the literature (Abad et al., 2020; Chao et al., 2016; Liu et al., 2019; Wang, 2020).

Content Design, or the design of information in the ITD model, includes tasks and procedures in the analysis and design stage of the ADDIE model (Liu & Velasquez -Bryant, 2003). Content design at course level mostly is the design of objective-oriented learning materials, learning-style-driven activities, or student-need-based guidance (Abad et al., 2020; Liu, Ripley, & Lee, 2016). Curriculum design is a higher level of content design that aims at the learning outcome from a program. Curriculum design commonly includes the structure of the curriculum, sequences of the courses, difficulty level, and assessment criteria and system, which employs a data-driven procedure of analysis, design and redesign (Méndez et al., 2014). At either the course or curriculum level of the content design, with or without assuming the new trends in content, the key is to perform the design in any perspectives to produce the expected outcomes.

Technology Design displays another dimension of the ITD model. First, needs assessment starts with estimating the cost, learning curve, accessibility, and other related issues (Liu & Velasquez-Bryant, 2003; Liu, Ripley, & Lee, 2016). Then decisions need to be made on: (a) the selection of technology tools, systems, or applications for certain types of the content information to be delivered (e.g., digital text, sounds, still pictures, videos, active stimulations, or 3-D illustrations), and (b) the selection of technology for communication or certain types of activities (e.g., team or individual work, online or in classroom, synchronous or asynchronous activities). Again, the design of technology aims at producing the desired learning outcomes (Liu et al., 2019).

Integration Design is where the integration of all three dimensions of the ITD model occurs. Integration design is the decision making on overall strategies, methods, and plans of the project, course, or program. It starts with the needs of learners, features of the subject content, objectives of the instruction, and the available resources (including faculty support and technology equipment). After all, the most critical work for the designer (the educator or researcher) is to integrate the content design and technology design into the overall plan and make the final and operational to-do list (Gagné et al., 2005; Liu & Velasquez -Bryant, 2003; Schlegel, 1995). All the listed tasks again aim to achieve the expected learning outcomes. In general, the three design related factors are about (a) setting the goals/objectives, and (b) designing all detailed operations to achieve the goals.

New Trends in Content. The new trends in content (*content curation*, *user-generated content,* and *microlearning conent*) are parallel with the needs and propensity of e-learning. Currently, social learning, learner-centered learning, and mobile learning are widely studied and practiced in SME learning (Becker & Park, 2011; Jeong et al., 2019). In a social learning environment, online or in-person, *content curation* is usually derived from the collaborative work or group work during the learning process (Cochrane et al., 2016). Learner-centered learning often produces *user-generated content* through individual and open-ended creative work (Smart et al., 2012; Tumkor, 2018). Furthermore, *microlearning* content with short sections of basic learning units operates well through mobile device (Beschorner & Hutchison, 2013; Bursztyn et al., 2015; Park & Kim, 2018). The current study explores the influence of the new trends in content on the outcomes of SME learning.

New Trends in Technology is mostly the use of *Immersive Technology* (e.g., AI, robotics, VR, AR, and MR) in teaching and learning. Educators used robotics to create integrated STEM instructions for middle school science classes (Ntemngwa & Oliver, 2018), and to increase girls' interest in engineering during early elementary studies (Sullivan & Bers, 2019). Artificial Intelligence (AI) has been used in teaching and research. For example, Goel and Joyner (2017) introduced their experiences of using AI to teach AI in an online AI class. Wang (2020) and Luan et al. (2020) promoted a new approach to use AI with model-driven big data analysis in education research, policy-making, and industry. Educators also introduced their experience of using virtual reality for children's memory training (Araiza-Alba et al., 2020), using augmented reality (AR) in mathematics learning (Cai et al., 2020), and using mixed reality (MR) mobile applications for personalized engineering education (Tumkor, 2018). Academic journals also launched special theme issues on VR, AR, and MR in education, for example, (a) on the theme of "Augmented and Virtual Reality in Education," by the *Journal of Educational Computing Research* (Beck, 2019), and (b) on the theme of "Immersive Virtual Reality in Education," by *British Journal of Educational Technology* (Bower & Jong, 2020). Both collected concurrent studies that reflect the "trends," and provide in-depth theoretical and practical guidance to educators and researchers. The current study explores whether such trends influence the outcomes of SME learning.

We have reviewed the three design related factors and two new-trends oriented factors. Next we are to review the two learning related factors, *Interactive Learning* and *Motivation.*

Interactive Learning. In interactive learning, learning and communication channels can be established by interactive and collaborative work (Wang, 2020). Interactive learning mainly emphasizes two-way communication between learner and instructor, learner and learner, and learner and the interactive media or system depending on the learning environment (Abad et al., 2020; Sahronih et al., 2019). For example, in an online course, the two-way communication can be achieved through online discussion or collaborative group work in the learning management system (Chen & Liu, 2018). Interactive media can be a program, software, or an AI/VR/AR application that interacts with learners (Cai et al., 2020; Yannier et al., 2020).

Learning occurs during the two-way interaction. Roman and coauthors (2020) examined the effect of using a digital tool (*Socrative*) to promote interactive learning in chemistry and chemical engineering studies. Sahronih et al. (2019) conducted a meta-analysis on 16 studies published from 14 journals during the period 2009 to 2018. In the

16 studies, the effect of using interactive media tools on students' science learning outcomes was examined, and the average effect size for Physics learning was 0.38 (n = 7 studies), for Chemistry learning was 0.45 (n = 2 studies), for Biology learning was 1.39 (n = 4 studies), and for integrated areas was 0.41 (n = 3 studies). The type of media that has the largest effect size was interactive multimedia (average effect size was 1.25, n = 5 studies). They calculated the effect size using Glass formula. Overall, when studying interactive learning, researchers mostly focused on (a) the method to conduct interactive learning, and (b) the interactive media to implement the interaction.

Motivation is a much emphasized factor in studies on learning, and is constantly found to have significant influence on learning, for example, flipped learning (Liu, Ripley & Lee, 2016), social media based learning (Liu et al., 2019), students' attitudes toward game-bases learning (Dini & Liu, 2017b), students' believes and performance in SME learning (Chao et al., 2016; Leaper et al., 2012). Another reason to include it in current study is to test the *consistency of its influence on learning outcomes* in SME learning and that in flipped learning (Liu, Ripley, & Lee, 2016) and social media based learning (Liu et al., 2019).

Summary of the Factors. In summary, the following seven factors are derived from the literature, including three design related factors (1, 2, and 3), two new trend oriented factors (4 and 5), and two learning related factors (6 and 7).

1. *Content Design (CD)*
2. *Technology Design (TD)*
3. *Integration Design (ID)*
4. *New Trends in Content (NTC)*
5. *New Trends in Technology (NTT)*
6. *Interactive Learning (InL)*
7. *Motivation (MO)*

Again, the purposes of this study are to identify significant factors to technology-based SME learning from published studies, and to determine the extent to which the factors can be used to predict successful technology-based SME learning. These seven factors are then examined in the following case analysis.

METHODOLOGY

RESEARCH QUESTIONS

Based on the purposes of the study, the case analysis was guided by the following research questions:

1. Can the probability that a technology-based SME learning case is successful be predicted by any of the seven explanatory variables — content design, technology design, integration design, new trends in content, new trends in technology, interactive learning, and motivation?
2. To what extent do the significant explanatory variables (if any from question 1) predict the probability of a technology-based SME learning case to be successful?

REFERENCE OF PRIORI POWER ANALYSIS AND THE SAMPLE SIZE

For the purpose of the case analysis and the research questions, logistic regression is the proper method for the data analysis. The appropriate sample size needs to be determined for a binary logistic regression with independent predictors, based on expected effect size.

In previous studies, the effect size measured by odds ratio for the predictors turned to be at least 1.5 (Catalano, 2015; Xu et al., 2019; Yen & Liu, 2009). With this reference, Liu et al. (2019) did the estimation of the sample size using *G*Power* 3.1.9.4, in which four values of odds ratios (1.5, 2.0, 2.5, and 3.0) were set to calculate the minimum sample sizes, resulting in the sample sizes of 637, 225, 134, and 96 for the four odds ratios respectively. That is, for example, if an expected odds ratio is between 2.0 and 1.5, a minimum sample size between 225 and 637 should be reasonable. In their study, they used a sample of 276 cases and achieved the odds ratios for seven predictors between 1.97 and 4.08 (Liu et al., 2019).

According to the study by Liu et al. (2019), we decided to obtain a sample with the size between 225 and 637 for logistic regression, expecting the odds ratios between 2.0 and 1.5 for the predictors.

THE SAMPLE

The sample of cases were selected from technology-based SME learning literature from 2008 to 2020. Originally, more than 340 refereed journal articles were screened including quantitative studies, qualitative studies, and project based studies. 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 and accurate information for the analysis: the learners, the learning subject, procedures of the technology-based SME learning experiences, and outcomes from the learners and their experiences.

Finally, 305 technology-based SME learning cases (articles) were selected from 140 peer-reviewed academic journals including regional, national and international journals. Referencing to the results from priori power analysis (Liu et al., 2019), 305 was considered a proper sample size for logistic regression with the expected odds ratios between 2.0 and 1.5 for the predictors.

In the 305 cases, 89.5% of them were from studies published between 2013 and 2020, and 10.5% of them from studies conducted between 2008 and 2012.

Among the 305 cases, 41.6% of the cases were studies in the area of mathematics learning, 44.6% in the area of science learning, and 13.8% in the area of engineering learning. In addition, 23.6% of the cases were studies at the first to sixth grade levels, 49.5% at the seventh to 12th grade levels, 22.6% at the undergraduate level, and 4.3% at the graduate level.

Technology use among the 305 cases ranged from learning management system for online learning (13.1%), social media (2.3%), instructional videos (6.6%), game and hypermedia applications (10.2%), interactive software or tools (12.5%), digital apps (10.2%), AI and Robotics (11.1%), VR-AR-MR (4.9%), mobile devices (18.0%), to other technology tools such as graphic analysis program, calculator, or digital organizers (11.1%).

PROCEDURES OF CASE ANALYSIS

The case analysis in previous studies (as listed in Table 1) and the current study took an approach to integrate both qualitative and quantitative methods. The procedures included identifying the case and relevant factors, measuring and analyzing the factors to achieve the purposes of the case analysis.

The Cases (from literature). One study from one published academic article was treated as one case. It can be a quantitative study, a qualitative study, or a project based report on using technology in SME learning. A case was identified from an article based on the descriptions provided by the authors, with accurate information such as the learners, the SME learning procedures, technology use, and learning outcomes.

What to Analyze (qualitative content analysis). The types of *object* to be analyzed can be factors, models, theoretical approach, methods of research design and data analysis, or treatment and outcomes. Decisions made were based on the purpose of the study. In the current study, seven factors of interests were identified, based on literature review, theoretical design models and a synthesis on the main themes presented in the 305 cases, to predict the SME learning.

Measurement and Coding. After the factors were determined, data coding was performed. In the current study, the categorical values (either 1 or 0) were assigned to the seven explanatory variables (CD, TD, ID, NTC, NTT, InL, and MO) and the response variable SME learning (SMEL).

Data Analysis. The purpose of the current study was to identify the explanatory variables, and determine if they can be used to predict the probability of a SME learning experience to be successful. Therefore, logistic regression was conducted for the data analysis.

VARIABLES EXAMINED AND CODING

Table 3 shows the coding for the response variable and explanatory variables. Details of the coding for each variable are presented below.

The Response Variable. Again, the purpose of the case analysis was to explore the factors or explanatory variables that influence the probability of a technology-based SME learning case to be successful as described in the literature. In this analysis, the response variable was *SME Learning* (SMEL). The SMEL 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) SMEL resulted in better learning outcomes if the outcomes were quantitatively measureable such as evaluation scores, (b) SMEL exhibited expected features in student learning performance if the outcomes were summarized from observations or qualitative data, or (c) SMEL showed positive trends in learning performance towards improved learning outcomes if the case was an on-going study or project based study. Otherwise, a value of zero was coded for an "unsuccessful" case for not producing expected outcomes.

Table 3. *Coding of the Response Variable and Seven Explanatory Variables*

Variables	**Values**	
(presented in articles)	**1**	**0**
Response Variable		
(*SMEL*) – SME Learning	Successful	Unsuccessful
Explanatory Variables:		
(*CD*) – Content Design	Yes	No
(*TD*) – Technology Design	Yes	No
(*ID*) – Integration Design	Yes	No
(*NTC*) – New Trends in Content	Yes	No
(*NTT*) – New Trends in Technology	Yes	No
(*InL*) – Interactive Learning	Yes	No
(*MO*) – Motivation	Yes	No

The Explanatory Variables. The seven factors summarized from the literature were explanatory variables (or predictor variables) in the data analysis. The following paragraphs explained how they were coded.

First, the three design related factors were *Content Design* (CD), *Technology Design* (TD), and *Integration Design* (ID). A code of 1 indicates that the instructional design principles, tasks and procedures (Gagné et al., 2005; Liu & Velasquez-Bryant, 2003; Schlegel, 1995) were employed and details were specifically explained in the article. If the features of content design were presented, the variable CD was coded as 1. If the tasks and procedures of technology design were described, the variable TD was coded as 1. If the models, procedures, or tasks of integration design were demonstrated, the variable ID was coded as 1. Overall, a case does not have to present all the tasks as referenced in the design models. It can be considered as "design presented" so long as the main tasks that fit the specific experiences of the case were described. Otherwise, a value of zero was given to code the variable as "design not presented" for the case.

Second, the two new trend oriented factors—*New Trends in Content* (NTC) and *New Trends in Technology* (NTT)—can be coded as 1 for a given case if any type of trends (listed in Table 2) was reflected in the case. For example, if microlearning, content curation, or user-generated content was reflected in the SME learning content, the variable NTC was coded as 1. If any type of the immersive technology (AI, Ro, VR, AR, or MR) was used in the SME learning, or any technology tools were examined with a new trend of learning, the variable NTT was coded as 1. Otherwise, a value of zero is given to code the variable as "new trends not presented" for the case.

Third, the other two learning related factors were *Interactive Learning* (InL), and *Motivation* (MO). If the article provided detailed descriptions of the strategies, methods, technology tools, activities, or models used to establish an interactive learning environment, or if interactive media, systems and apps were examined for effectiveness, the variable InL was coded as 1. If the case reflected the strategies, methods, activities, technology use, or learning material selection that actively motivate students' technology-based SME learning, the variable MO was coded as 1. Otherwise, a value of zero was given for the absence of those features in a variable.

DATA ANALYSIS AND RESULTS

DESCRIPTIVE RESULTS

Logistic regression analyses were conducted to determine whether *Content Design* (CD), *Technology Design* (TD), *Integration Design* (ID), *New Trends in Content* (NTC), *New Trends in Technology* (NTT), *Interactive Learning* (InL), *and Motivation* (MO) could be used to predict the success of a technology-based SME learning case (Case Success). The assumptions of logistic regression were checked and no violations were found. Frequencies for each variable are shown in Table 4.

Table 4. *Frequency Distributions of the Response Variable and Seven Explanatory Variables*

Variables	**Values**	
	1	**0**
Response Variable		
(*SMEL*) – SME Learning	194	111
Explanatory Variables:		
(*CD*) – Content Design	170	135
(*TD*) – Technology Design	186	119
(*ID*) – Integration Design	208	97
(*NTC*) – New Trends in Content	156	149
(*NTT*) – New Trends in Technology	190	115
(*InL*) – Interactive Learning	164	141
(*MO*) – Motivation	179	126

LOGISTIC REGRESSION RESULTS

First, a logistic regression analysis was performed with all seven explanatory variables. The results showed that the model was significant (χ^2 = 88.958, *df* = 7, *p* < .001), but two of the seven variables did not significantly contribute to the model: *New Trends in Content* (Wald χ^2 = 1.160, *p* = .281) and *New Trends in Technology* (Wald χ^2 = 2.703, *p* = .100). Therefore, these two variables were eliminated from the model in the next model examination. The five explanatory variables included in the next logistic regression analysis were: *Content Design* (CD), *Technology Design* (TD), *Integration Design* (ID), *Interactive Learning* (InL), and *Motivation* (MO).

Results from the second logistic regression showed that the second model with these five explanatory variables were significant (χ^2 = 84.783, *df* = 5, *p* < .001) and accounted for about 33% of the variation in the response variable (Nagelkerke R^2 = .332), indicating that this model significantly predicts group membership. The Hosmer and Lemeshow Goodness-of-Fit Statistic of 5.632 (*p* = .689) was not significant, indicating that the model provides a good fit of data. Specifically, 64 out of 111 unsuccessful cases (57.6%), 168 out of 194 successful cases (86.5%), and a total of 232 out of 305 cases (76.1%) were correctly predicted by the model.

Table 5. *Logistic Regression Outputs of the Five Explanatory Variables*

Variables	**DF**	**Parameter Estimate**	**Standard Error**	**Wald χ^2**	***P***	**Odds Ratio**
(CD)	1	0.643	0.282	5.203	.023	1.903
(TD)	1	1.058	0.283	14.024	<.001	2.882
(ID)	1	1.074	0.289	13.833	<.001	2.928
(InL)	1	0.648	0.282	5.293	.021	1.912
(MO)	1	1.114	0.281	15.686	<.001	3.045
Constant	1	-2.022	0.351	13.566	<.001	0.132

Response variable: SME Learning (SMEL),
Explanatory variables: Content Design (CD), Technology Design (TD),
Integration Design (ID), Interactive Learning (InL), and Motivation (MO)

A significant Wald χ^2 value for a given variable indicates that the variable is significantly related to the response variable. As shown in Table 5, the Wald χ^2 values are significant for all five explanatory variables. Therefore, all five explanatory variables are included in the model equation. The Parameter Estimate generates the estimated coefficients of the fitted logistic regression model, and they are used to formulate the following logistic regression equation (1):

$$\text{logit}\ (\hat{p}) = -2.022 + 0.643(CD) + 1.058(TD) + 1.074(ID) + 0.648(InL) + 1.114(MO) \text{ ----- } (1)$$

The sign ($\hat{p}$) indicates an estimated probability value (also called *log odds*) for the response variable (SME Learning) to be 1, 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, given the same values on the other explanatory variables, when the variable InL (*Interactive Learning*) is 1 (that is, when interactive learning strategies or activities are applied in the SME learning experience), the logit transformation of event probability (that the SME learning case to be successful as described in the literature) increases by 0.648 (see Table 5). The estimated coefficients for the other four explanatory variables can be interpreted in the same way.

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 InL (*Interactive Learning*) is 1.912 (see Table 5), indicating that an SME learning case would be 1.912 times more likely to be successful if interactive learning is engaged in the case, compared with cases that do not engage active learning. If the odds ratio is smaller than 1, the probability of the response variable being 1 decreases (that is, the probability of an SME learning case to be successful decreases when that explanatory variable exists). As seen in Table 5, all five odds ratio values are larger than 1 (ranging from 1.903 to 3.045). Therefore, all five variables positively contribute to the success of a technology based SME learning case.

SUMMARY OF THE RESULTS

In summary, all the three design-related variables (*Content Design, Technology Design,* and *Integration Design*) and two learning-related variables (*Interactive Learning,* and *Motivation*) significantly contributed to the model, and positively associated with the success of a technology-based SME learning (SMEL) case. That is, the probability of a SMEL case to be successful increases when (a) the relevant principles and tasks of instructional design and technology integration for the three design-related variables are employed, and (b) interactive learning environment and activities to motivate learning were provided. However, the two new-trend oriented variables were not significant, although they were highly advocated in the field and literature. In the next section we present an in-depth explanation of the model and how it can be used in research and practice.

COMPREHENSIONS OF THE PREDICTIVE MODEL

This section summarizes the static prediction model developed from the current study, the specific attributes of the static prediction model, and a new proposed dynamic prediction model for research and practice.

THE STATIC PREDICTIVE MODEL FUNCTION

According to the results from the logistics regression and the relationships between the five explanatory variables and the response variable, a predictive model can be summarized into the following model function equation (2) as shown in Figure 1.

P (SMEL=1) = *f* [CD, TD, ID, InL, MO] ------------------------------------ (2)

Where:
SMEL = SME Learning
P (SMEL=1) = Probability of SMEL to be successful
***f* […]** indicates "a function of …"
CD = Content Design, **TD** = Technology Design, **ID** = Integration Design,
InL = Interactive Learning, **MO** = Motivation

Figure 1. Static predictive model function of SME learning.

Model function (2) reads "the probability of a SMEL case to be successful is a function of content design, technology design, integration design, interactive learning, and motivation." It exhibits the relations between the group of explanatory variables and the response variable. Logistic regression equation (1) in the section Data Analysis and Results is a concrete model that describes all specific predictive relations or influences. This model function (2) presents is a conceptual model derived from the 305 cases.

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

ATTRIBUTES OF THE STATIC PREDICTIVE MODEL

As described above in the section Data Analysis and Results, odds ratio can be used to explain the contribution of an explanatory variable to the model. For example, the odds ratio for variable *Interactive Learning* is 1.912 (see Table 5), indicating that an SME learning case would be 1.912 times more likely to be successful if interactive learning environment and/or activities are provided to the learners, compared with cases in which interactive learning activities are not engaged. Next, we explain how to calculate the contribution of one or certain variables 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* when certain explanatory variables are included. The *log odds* then can be converted into the probability of the SMEL case to be successful, P(SMEL=1). For example, when all five 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):
   log odds = −2.022 + 0.643*1 + 1.058*1 + 1.074*1 + 0.648*1 + 1.114*1 = 2.515
2. Calculating *odds*:
   odds = exp (2.515) = 12.366 (exp stands for *exponential function*)
3. Converting odds to probability:
   P(SMEL=1) = 12.366 / (1 + 12.366) = 0.925

That is, when all five explanatory variables are considered in the case (when each is coded as 1), the probability of an SMEL case to be successful is .92.

If an explanatory variable is absent, it is coded as 0. For example, given 1 was assigned to the other four explanatory variables, if the *Motivation* was not promoted in the case as described in the article, then the term of *Motivatio*n in equation will be (1.114*0) and equal to 0. Using equation (1), we can obtain the results as: the *log odds* is 1.401, the *odds* = exp (1.401) = 4.059, and the P(SMEL=1) = .802. That is, when Motivation is absent, the probability of an SMEL case to be successful is .802 with the other four explanatory variables in the model.

We can compare the calculated probabilities with different combinations of the explanatory variables and explain in-depth comprehensions of the model.

THE DYNAMIC PREDICTIVE MODEL

The predictive model in Figure 1 is a static model, as we treat each of the five explanatory variables as a single variable, and the success of a SMEL is a function of the combination of the five single variables, where each variable has a single value of 1 or 0. With the idea of dynamic design (Liu et al., 2019), if we measure each of the variables from multiple dimensions, with dynamic data in a developmental approach, each of the five variables can be a function of a set of other relevant variables. For example, in the static model, *Content Design* is a variable indicating the existence or absence of the components such as content analysis, design of content information, or development of a set of basic learning units and tasks. It is coded as 1 or 0. However, if we have an assessment system to measure each of the components under the variable, *Content Design* 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 can be expanded into a dynamic model, indicating the function of functions as expressed in Figure 2, with model function equation (3).

P (SMEL=1) = F{ *f(CD), f(TD), f(ID), f(InL), f(MO), f(T)*} -------------------- (3)

Where:
SMEL = SME Learning **P (SMEL=1) =** Probability of SMEL to be successful
f(…) indicates "a function of …" **F {…}** indicates "the function of ***functions***"
CD = Content Design**, TD =** Technology Design**, ID =** Integration Design,
InL = Interactive Learning**, MO =** Motivation, **T** = Time

Figure 2. Dynamic predictive model function of SME learning.

Model function (3) reads "the probability of a SMEL case to be successful is the ***function of a set of sub-functions***, including the functions of *Content Design, Technology Design, Integration Design, Interactive Learning, Motivation,* 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" (Liu et al., 2019; Schöner et al., 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 six sub-functions can be studied, and such studies would provide multiple-dimensional framework or directions for us to design and examine dynamic learning.

DISCUSSION AND CONCLUSION

In summary, we have reviewed the studies in technology based SME learning, and conducted a case analysis on 305 studies, from which a static predictive model was generated with five variables that positively associated with the success of a technology based SME learning case. We also provided directions in using the static predictive model to explore a better way of SME teaching and learning, based on which a dynamic predictive model was formulated for further research and practice.

We have reached the following conclusions: (a) findings are consistent with the literature in terms of the influential factors and effect size, (b) non-significant new-trend oriented factors highlight the issues of design in technology integration again, (c) the dynamic design model supports data-driven teaching and learning with challenges, and (d) there is an integrative approach among the learning of science, mathematics, and engineering.

CONSISTENCY OF THE FINDINGS WITH LITERATURE

The Influential Factors. The three design related factors—*Content Design* (CD), *Technology Design* (TD), and *Integration Design* (ID)—are found significant to technology based SME learning, demonstrating the consistent results with the four studies in the literature (as listed in Table 1). Different from some specific influential factors found in other studies, for example, *active learning* in Liu, Ripley and Lee's study (2016) with 216 flipped learning cases, and *collaborative learning* and *active learning* in Liu et al.'s (2019) study with 276 social media based learning cases, the current study with 305 cases also finds *interactive learning* to be significant. Consistent with these two studies, current study does find *motivation* significant. The results are as expected that the three design related factors are significantly influencing SME learning outcomes, which concludes to our believe that design is the basic of basics for technology integrated teaching and learning.

Effect Size. In a logistics regression analysis, odds ratio is the effect size that explains the contribution of a predictor to the model. In this study, odds ratios of the five predictors ranged from 1.903 to 3.045 (see Table 5), indicating their positive influence on the probability of a SMEL case to be successful.

The range of effect sizes from similar studies in the literature can provide a general reference to our study – the extent to which our findings are consistent with the literature. The odds ratios for the predictor variables from the four similar studies listed in Table 1 range from 12.9 to 21.07 (Liu & Maddux, 2008), 2.166 to 2.497 (Liu, Ripley, & Lee, 2016), 2.286 to 2.741 (Liu, Li, & Shcherer, 2016), and 1.965 to 4.083 (Liu et al., 2019), with a minimum of 1.965 and maximum of 21.07. In addition, Catalano (2015) suggests that the odds ratio of knowledge transfer when a student studies in a situated learning environment is 2.9. Xu et al. (2019) reports the odds ratios (from 0.02 to 49.673 for seven explanatory variables) for a student to have positive perception of teaching effectiveness. The odds ratios of the five explanatory variables in the current study (from 1.903 to 3.045) are right within the range as showed in the literature.

Moreover, in a logistics regression analysis, the model effect size R^2 specifies the percentage of the variation in the response variable that can be accounted by the model. The Nagelkerke R^2 for this study is .33, indicating that the model explains 33% of the variation in response variable (the possibility of an SME learning case to be successful). It is within the range of Nagelkerke R^2s for the four studies (between .25 and .66) as listed in Table 1.

In summary, the results from current study are consistent with the literature in terms of the influential factors and the effect size.

NEW TRENDS AND DESIGN

It is unexpected that the two new trend orientated factors (*New Trends in Content*, and *New Trends in Technology*) were not significant, as they were very highly advocated in the field of e-learning. One explanation might be that they were examined with a combination of other five explanatory variables, and the variance of these two variables may not be enough to make them significant. Results might be different if they are examined separately or combining with some other variables. Since the main framework of this study is the ITD and ADDIE model, we did not examine these two new trend oriented variables separately without the presence of the design related variables. Further studies can be conducted to examine them with other learning related variables.

This non-significant phenomenon brings up the issue in design again. When certain learning content in new trend was used in a case, did the researcher(s) conduct content design? When certain immersive technology in new trends was applied in a case, did the researcher(s) conduct technology design? The descriptive results showed that among the 305 cases, 32% (98 out of 305 cases) applied the format of content in new trends (such as microlearning or content curation) with content design procedures, and 19% (58 out of 305 cases) with no descriptions about content design. Furthermore, 42% (130 out of 305 cases) used the immersive technology in new trends (such as AI, Ro, VR, AR or other tools in new trends) with descriptions of technology design, and 19% (60 out of 305 cases) with no descriptions of technology design. Although these two variables (*New Trends in Content*, and *New Trends in Technology*) were not significant, there evidently is a positive propensity that more educators and researchers did start to consider the two very critical factors (*Content Design* and *Technology Design*) while adopting the new trend oriented content and technology into SME teaching and learning.

DYNAMIC MODEL AND DATA-DRIVEN APPROACH: CHALLENGES

One of the new trends in e-learning is data-driven teaching and learning, using big data analytics to create or adjust educational content that meets with individual learners' needs (Walker, 2021). The dynamic design model formulated in this study provides a conceptual framework and specific guides for data-driven SME learning. The key point is using this model to generate dynamic data and perform dynamic assessment (Liu et al., 2017; Liu, Han et al., 2019) on learner performance, for example,

a. on SME learning content (with the objectives set under ***f(CD),*** the function of contend design), to see how well a student learns to achieve the learning objectives, or
b. on motivation, to see whether the SME learning activities or environment motivate the student learning as they were designed (with the objectives set under ***f(MO),*** the function of motivation), and
c. at any given time point (with the time units set under ***f(T),*** the function of time).

One challenge to perform this dynamic assessment is the work on the system used to generate the dynamic data over time, as the functions, parameters, and all necessary algorithms need to input to the system. It can be an online learning management system. However, not all the systems allow an individual instructor to do so.

Currently artificial intelligence (AI) applications are available for education. Some of them are used to assist and support learning, providing a VR or MR learning environment (Yannier et al., 2020). Some have started this data-driven approach to collect dynamic data (Méndez et al., 2014). Nevertheless, building an AI learning environment that can generate the desired dynamic data is beyond the professional scope of an educator who is not in the area of computer science and engineering. All the new trends in e-learning (as listed in Table 2) would promote one new trend along the road – the high demand on inter-disciplinary collaboration.

INTEGRATIVE APPROACHES AMONG S-M-E

In the literature of SME learning, some studies were conducted to examine STEM learning as a combined focus (Seage & Türegün, 2020), and some pursued an integrative approach to analyze studies on technology-based learning in science, mathematics and engineering together (Becker & Park, 2011; Roman et al., 2021). This study employed such integrative approach. We selected technology-based learning cases in all three areas and analyzed them together to find out the similar features that influence the SME learning in common. Although the format of content, means of content delivery, requirement of hands-on activities, even the methods of assessment may differ in many ways among the three subject areas, the case analysis produced the results in an S-M-E integrative approach that *Content Design, Technology Design, Integration Design, Interactive Learning* and *Motivation* were the significant factors that associated with the probability of learning cases to be successful across the three areas.

The term *integration* discussed here does not mean a simple *addition* to add or combine all the relevant components together. Integration is the procedures to take advantages of the knowledge, skills, strategies, and mostly the way of thinking in one area to benefit or improve the learning in another area (Liu & Velasquez-Bryant, 2003). Waterman et al. (2019) reported a study in which they integrated computational thinking into the core curriculum of elementary science and mathematics. The framework of Massachusetts Digital Literacy and Computer Science identified five topics within the strand of computational thinking: (a) Abstraction, (b) Algorithms, (c) Data, (d) Modeling and simulation, and (e) Programming and development. The first four topics were integrated into the third-grade science and mathematics learning materials, which also addressed the standards of science, mathematics and computer science at the third grade level. With well-designed integrative learning materials and activities, the experiences showed promise that students did demonstrate both computational thinking and deeper science or mathematics understanding (Waterman et al., 2019). This is a typical case of the S-M-E integration.

Early in 2001, Liu and Cummings conducted an interesting study to integrate *Logo* programming into children's mathematics and geometry learning. The results showed that children (aged from 6 to 9 years old) were motivated to learn mathematics and geometry concepts, and demonstrated mathematical thinking and geometric thinking with integrated learning materials and activities that required a hierarchical procedure of *concrete-abstract-concrete* thinking (Liu & Cummings, 2001). Some other such integrative studies were also found in the literature, such as the integration of science and mathematics at secondary school level (Prieto et al., 2019), chemistry and chemical engineering studies at university level (Roman et al., 2021), among the four areas of STEM (Becker & Park, 2011; Shirey, 2018). The studies over years showed positive outcomes. Those promising research findings have provided a solid foundation and support to the idea and method we carried out for the current study – to examine technology-based learning across the three areas of S-M-E together based on this integrative approach.

LIMITATION AND FURTHER STUDIES

One limitation of this study is that the case analysis was based on the data coded from the literature, purely according to the descriptions in the articles. In some studies, the experimental conditions or case settings were described in general without in-depth details. The five predictor variables were clearly presented in some cases, but were ambiguous in some other cases. Some of the studies may or may not be duplicable. Therefore, the results from the case analysis can only provide a reference for further research and practice. More studies are expected to continue.

Although the results and the predictive model are based on the literature in SME learning, they may still be applied in a general education setting. We hope that the literature review and findings from this study could provide useful reference to other researchers and generate more research ideas. Next, some studies can be continued to (a) examine the validity and reliability of the predictive model with larger size of first hand data, or in other learning areas, (b) examine the effectiveness of using this model on student learning with experimental design, or (c) explore more relevant factors in new trends of e-learning.

We have also generated some new thoughts about further studies. First, it is worth of exploring the SME learning at K-12 levels and the university level separately and then comparing the models. It is interesting to see the same or different predictors for SME learners at different levels, and the same or different ways to conduct instructional design to improve SME learning at different levels. We believe that results from such studies will provide more insights to educators at different levels. Second, with the integrative approaches, we have a lot to learn about the integrations (a) among technology platforms, (b) among multiple styles of learning, (c) between static design and dynamic design, (d) among different models of design, (e) among different *trends*, or (f) of different methods of data analytics. Any of these topics can be the theme of a new study. We hope we can learn more through our future research and practice.

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