Industry 4.0 and higher education: Combining learning analytics and learning science to transform the undergraduate learning experience in Vietnam

Ray Webster, John Andre and Trinh Thi Thu Giang
National Economics University, Hanoi, Vietnam
Corresponding author: raywebster@isneu.org

ABSTRACT

This paper will discuss the potential impacts of applying AI techniques and digital technologies such as learning analytics to enhance undergraduate education and graduate employment in Vietnam in the context of the fourth industrial revolution. It will argue that it is necessary for us, as educators, to consider integrating these developments with key learning science advances in our understanding of individual and personalised learning. This approach will complement the undeniable advantages that learning analytics will bring to the management of higher education. The different levels of experience of several other regional nations in the development and implementation of learning analytics systems will be considered. These will be reviewed with particular reference to those implemented through learning management systems such as Blackboard and Moodle, as the latter systems are already in use at the authors' parent institution. An applied research project, drawing on the authors' considerable experience in systems development and learning research will then be outlined. The project's aims include the integration and implementation of learning analytics techniques with the products of previous research projects in self-regulated learning and personal learning environments. A student-centred reflective and participatory methodology will be used to ensure full student involvement in the design and development process. It is intended that the combination of this methodology with the use of learning analytics tools and techniques will help produce a personalised learning support system that will primarily enhance student learning, but will also produce valuable individual and aggregate learner information for university managers.

1. Introduction

As discussed in a related conference paper (Andre el al, 2019) several of ASEAN's member nations face infrastructure and data sharing issues when planning the implementation of networked learning analytics systems in higher education. This paper suggests a bottom-up approach of implementing such systems by using a free open source learning management system (Moodle) that generates and captures the learning analytics data from student activities. By integrating this approach with a tried and tested user-centred methodology for enhancing personalised learning (RAPAL) it is hoped to produce a practical and standardised and low-cost solution to the problem of introducing effective enhanced learning analytics systems into universities in Vietnam.

The power and potential of big data and learning analytics to help transform higher education has emerged over the past decade as a rapidly growing field. Levels of development and implementation (as against extensive discussion) vary enormously between countries and are often related to the available technological infrastructure, data integration, national levels of prosperity and development, and the awareness and commitment of political and educational leaders. As the term learning analytics implies, the two main areas of research are those of data analysis and the practical implementation of theories of learning. These are two skill sets that are not always part of the resource set of researchers and practitioners. A recent major study of research projects and publications on educational theories and learning analytics (Wong et al, 2018) concluded that:

> *"learning analyst(s) may be proficient with analytical approaches, they may be less familiar with the nuances of learning. Similarly, learning scientist(s) may be apt at recognising the nuances of learning but not equipped with skills to perform the analytics using trace data".* (Wong et al, 2018)

For this proposed project, both authors have extensive experience of information systems, data analysis and educational research, while working and teaching at universities in Vietnam, England and Australia. Consequently, it is hoped that by combining and applying their experience, a prototype of a personalised learning analytics system as a taught module/unit will be implemented at a major university in Vietnams the next academic year (2019-20). The project, as outlined in the later stages of this paper, will therefore be a "*joint effort of learning scientists and learning analysts in conducting research that integrate learning theories and learning analytics.",* as suggested by Wong et al (2018)

1.1The Fourth Industrial Revolution, applying digital technologies and big data analytics

In September 2018 Vietnam hosted the World Economic Forum on ASEAN 2018 (WEF ASEAN 2018) in Hanoi. Prime Minister Nguyễn Xuân Phúc of Vietnam met with Prime Minister Lee Hsien Loong of Singapore and after praising Singapore's economic and technological accomplishments, commented that he hoped that Singapore would help Vietnam to:

> *"grasp opportunities brought by the fourth industrial revolution, apply digital technology in governance and urbanisation process, transfer technologies, and develop software parks and start-up centres."* (Vietnam News, 2018)

This is a sound approach as Singapore has one of the most advanced economies in the world, not just in ASEAN. In terms of applying digital technologies, one of the key areas that has emerged and prospered for businesses over the past decade is the use of data analytics. In a presentation on emerging trends and business opportunities from big data analytics, Scott Likens of PwC China commented that:

> *Although we have a huge amount of data, the key point is how to transform data into insights and intelligence, deliver when and where they're needed to make and implement better strategic and operational decisions*," (Likens, 2018)

This is the next step for businesses, where the traditional top down approach to analytics of predicting future patterns of activity using past data will be replaced by modelling behaviour at an individual level using "*behavior and macro-economic drivers."* Likens and PwC predict that this will result in better increased profitability driven by better decision making and improved products. While the business sector – especially in fields like finance and HRM - have long used data analytics to enhance decision making the education sector, including most higher education sectors have been much slower in adopting this strategy.

1.2 Learn, unlearn, relearn!

On the business and education fronts, the phrase "learn, unlearn, relearn" has become a mantra for adaptability and constant change recently. However, the then Permanent Secretary of Singapore's Manpower Ministry, Loh Khum Yean has been promoting this viewpoint with reference to lifelong learning since at least 2009 (Maine, 2011).

The challenges that face the city state of 5 million people at a different stage of development and modernisation are considerably different from those of a nation a population of 100 million people. However, when Tan Thiam Soon, the president of Singapore Institute of Technology (*which describes itself as "Singapore's university of applied learning*") comments that '*If we don't get this right, we are in trouble,*' and '*No amount of formal education is ever going to be enough*' (Ross, 2018) then there is a serious implication that we have to radically revise our approach to learning and teaching. One of Singapore's social initiatives for putting into practice its ""learn, unlearn, relearn" philosophy is to provide all citizens with a "learning credit account" of S$500 to enable them to return to education and learn new skills. Combining learning andalytics and learning science approaches for new learning solutions is a more yechnology focused initiative.

1.3 ASEAN partners: education and learning analytics

A 2017 report by the Asian Development Bank - "ASEAN at 50: What does the Fourth Industrial Revolution mean for ASEAN Economic Integration?" - (Goswami et al, 2017), pointed out that in terms of government strategies for the development of technology-literate human capital, *"only Singapore, Malaysia and the Philippines have digital strategies."* The authors stated that when considering the overall education systems, traditional school curriculums remained largely in place with insufficient ICT equipment for students. This is also reflected in the different levels of experience of the ASEAN regional nations in terms of the development and implementation of learning analytics systems.

This combination of digital strategies and educational systems means that Vietnam's ASEAN partners also vary widely in their recent development of learning analytic systems. A series of papers (Lim & Tinio, 2018, eds.) provides a comprehensive overview of the challenges facing countries in adopting learning analytics systems in education. The editors introduce the book by asking a series of questions that explore the issues that need to be addressed by all countries with reference to the implementation of learning analytics in universities. These questions are considered in detail terms of Vietnam in a related SEAMEO 2019 conference paper by the authors and a Vietnamese colleague (Andre et al 2019). The experiences of several ASEAN partners are briefly reviewed below.

1.3.1 Combining learning analytics and student attributes

In terms of learning analytics and improved student learning, a project at the University of the Phillipines Open University (Reyes, 2018) has taken a broader approach. It has considered methods and data sources for of improving student learning based on attributes other than learning analytic measured academic behaviours. These factors included demographic attributes and the completion of a course aimed at reorienting students towards the differences between traditional and distance learning courses. Developing student support systems by considering alternative measures, e.g. learning profile attributes and Flexible Student Alignment, is recognized as an issue of key importance by the current authors (Webster & Andre, 2018).

In Malaysia, the Moodle LMS has been successfully introduced into public and private sector universities for a number of years (Hoh et al, 2011). The original home of Moodle LMS is Curtin University in Perth, Western Australia where Martin Dougiamas, inventor and author of Moodle (and the founder and CEO of Moodle Pty Ltd) studied and worked while developing the system. Malaysia hosts the largest international campus of Curtin University at Miri in Sarawak where Moodle and its learning analytics systems are extensively used.

1.3.2 Singapore's expereinces

If we look at ASEAN we can get a sense of the great variation in the development of digital economies and the use of AI tools and techniques, including analytics, throughout the community. Singapore is recognised as a world leader in education and the Nanyang Technological University (home of Singapore's National Institute Education - NIE) is quickly moving ahead with the use of learning analytics and big data to improve educational outcomes. NIE, using the Blackboard LMS, already runs regular staff seminars aimed at increasing staff awareness of the implications of the introduction of big data and learning analytics for education and employment in general and NIE's academic programs in particular.

The Blackboard LMS learning analytics features are already in use in the NTU learning environment in Singapore. NTU states that these learning analytics capabilities help administrators and teaching staff to monitor the learning and academic performance of the students. They also suggest that students benefit from their own abilities to look at how they are doing on the courses they are taking and compare their performance with that of other students (NTU, 2018).

Further afield and in an interesting study reviewing and attempting to replicate the results of several previous learning analytics studies, Mwalumbwe and Mtebe (2017) presented contrasting results. Active learning features such as interaction with peers, contributing discussion posts and completing set exercises were found to have a significant impact on students' learning performance. However, the study reported that easily measured (and often reported) actions such as the frequency of logging in, time spent in the LMS and the number of downloads had *"no significant impact on students' learning performance"* (Mwalumbwe &Mtebe, 2017). Contributing to discussion forums and interacting with peers had the greatest impact. This is of relevance to the design of module delivery for the proposed research project as, in the eight years of using Moodle at on the undergraduate programs of ISME at NEU, students have been reluctant to post in the forums provided (preferring to talk online elsewhere in Vietnamese). However, although the prototype module is being implemented within an English language partnership program, the resultant model should be implementable in any language.

2. Integrating learning analytics and learning science

We argue that for real advances in student learning to take place, researchers must also consider how to enable students to understand and improve the personal and individual aspects of their own learning – not just respond to learning patterns from learning analytics. At one of NIE's staff seminars in April 2018, one speaker discussed the implications of learning analytics and other AI innovations for higher education (Siemens, 2018). The speaker emphasised the need for students to enhance their soft skills such as creativity and critical thinking to improve their self-regulated learning capabilities. The importance of these human skills for future employability as well as for improved learning will increase in the coming years.

This perspective is also emphasized by several researchers, for example, Chatti & Muslim (2019) and Thille & Zimmaro (2017), who state that for real improvements in learning, we need to combine data analytics with developments in learning science to produce more effective gains in the advances in self-directed and lifelong learning. The diagram below expands and demonstrates this theme.

Thille had earlier illustrated this point by providing examples of data driven (learning and analytics) and learning science driven (cognitive science and metacognition) inputs into creating explanatory and predictive models as shown in Figure 2 (Thille, 2015).

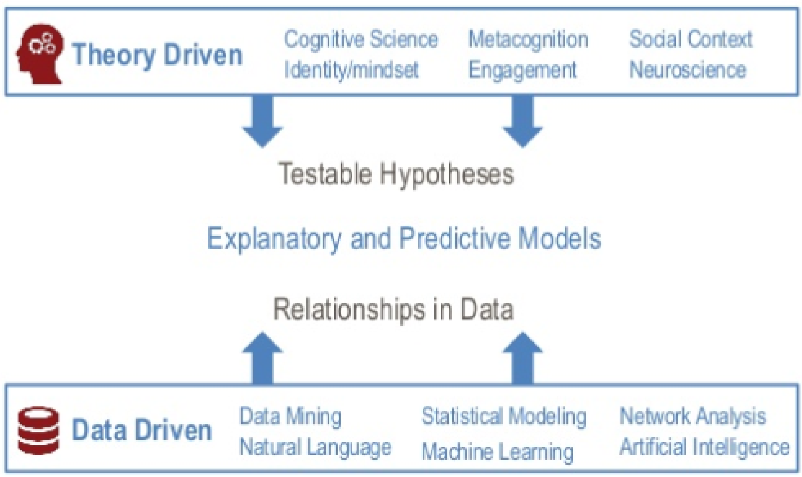

Figure 1: Data driven and learning science driven inputs for explanatory and predictive models (Thille, 2015)

The next section explores a proposal to develop and implement a system providing such models and methods for higher education students in Vietnam (although the authors firmly believe that these proposals can be implemented in years 10-12 for high school students). It provides a bottom up approach that aims to overcome the barriers to effective learning enhancement using learning analytics outlined by Lim and Tinio (2018).

2.1 Methodologies for combining learning analytics and learning science: RAPAL and PERLA.

The theoretical models that underpin this work are provided by the RAPAL methodology (Webster & Andre, 2018; Webster, 2009) and the PERLA framework (Chatti & Muslim, 2019). The authors have developed and implemented RAPAL (Reflective And Participative Approach to Learning) to help put into practice personalised learning and self-directed learning on a range of undergraduate courses over the past fifteen years (Webster & Andre, 2018; Webster, 2005, 2009, 2016). The PERLA framework (Personalization and Learning Analytics) has been recently developed to provide a framework that enables the blending and integration of personalisation and at learning analytics and also draws on the authors' longer term interest and involvement in the area of personalisation (Chatti, 2010).

After reviewing a series of personalised learning models, Chatti and Muslim comment that despite the differences between the models, all of them include three specific phases. These phases are goal setting, execution and evaluation. Goal setting includes activities such as task analysis, planning and the activation of goals, while execution is concerned with the performance and processing of the learning task. The evaluation phase is comprised of important activities such as monitoring and controlling and providing feedback and self-reflection. In the RAPAL model and methodology SWOT analysis for goal setting has been combined with a professional development framework (goals- objectives, methods, timeframe, monitoring and reviewing) to develop of learning strategies within the context of each student's personal learning profile.

By integrating the cyclical process of personalization with the seven stages identified by Norman (2017) as being key to the design of usable services and products, PERLA produces a seven stage personalised learning activity cycle as a user centred design methodology. PERLA's seven stages of the personalized learning activity cycle consist of setting a goal related to a learning activity and then in the execution phase planning, specifying and performing the learning activity. The evaluation phase consists of perceiving the results, interpreting the results and then comparing this outcome with the goals set. The execution phase provides feedforward indicators while the evaluation phase provides feedback indicators.

PERLA then integrates the seven stages with the learning analytics cycle (*iteratively: Learning activity, Data collection, Data storage and processing, Analysis, Visualization, Action*) and produces a method for interrogating the user or student at each stage of the movement from learning goal to learning outcome. This interrogation produces the learning related indicators that provide the learning analytics data (see Table 1)..

Chatti and Muslim (2018, p256) provide an example of applying the seven stages of the personalised learning activity cycle in which the goal is active participation in a MOOC.

	Stages	**Indicators**	**Indicator objectives**
	Goal: Active participation in the MOOC • What do I want to accomplish?	• Top 10 contributors in the MOOC.	Motivation
Execution	**Plan** • What are alternatives?	• Overview of activities in the different collaboration modules of the platform (discussion forums, peer- reviews, annotations, etc.).	Awareness
	Specify • What can I do?	• Most active threads in discussion forums. • Most annotated learning resources. • Most discussed topics. • Reminder for peer-review deadlines. • Newsfeed.	Recommendation Awareness
	Perform • How do I do it?	• Show top rated annotations to be used as reference.	Recommendation
Evaluation	**Perceive** • What are the results?	• Statistics on performed collaboration activities (annotations, peer-reviews, posts in discussion forums, ratings, etc.).	Monitoring
	Interpret • What does it mean?	• Clustering/classification of participants based on their activities (number of posts, ratings, peer-reviews, annotations, etc.). • Show position in the social network based on the collaboration activities.	Self-reflection Feedback Assessment
	Compare • Is this what I wanted?	• Scale showing contribution status against the specified goal.	Motivation

Table 1: Applying the Seven Stages of the Personalized Learning Activity Cycle to Generate Indicators in a MOOC (Source: Chatti &Muslim, 2019 ,p256)

2.2 Learning profiles for autonomous learning

RAPAL has consistently used the concept of a learning profile to help implement the reflective goals set in the strategic learning development plans. Each learning profile also helps the individual student to better understand his or her own learning preferences and actions. The theoretical construct was derived from Jonassen and Grabowski's statement that: "*The particular combination of aptitudes and traits possessed by each individual is reflected in the individual's cognitive styles, personality, and learning styles.*"

After initially being developed as a reflective design methodology for the design of individual learning environments, the focus shifted to helping student to better understand and perhaps change their conceptions of learning and how to become an independent, self-directed learner. This was achieved using a modified methodology which, while using the same learning profile components, shifted the focus to a set of learning strategies (e.g. assignment, unit, semester, academic year) with goals, objectives, methods, timescales and monitoring and reviewing activities as part of the development planning process. However, the design and implementation focus was always maintained. This was achieved by requiring all learners to develop and implement an e-portfolio or as learning environment. The focus however shifted from the design of the learning environment to the design and understanding of the learning activities detailed in the e-portfolio.

With this approach, the RAPAL methodology overlaps and duplicates elements of the PERLA cycle in terms of personalisation and goal setting to generate learning analytics data through learning task choice, execution and evaluation.

The nature of the learning tasks involving individual students (working alone or in learning support groups) to produce learning strategies and individual learning environments was suited to the three instrument learning profile. It was considered to be sufficient given that the main analysis, reflection and processing was done by the individual student – supported by tutor and learning support group members.

3. Integrating the RAPAL and PERLA approaches within Moodle.

The enormous expansion of the processing and analysis power provided by the introduction of learning analytics allows us to expand the learning profile to consider additional elements. These factors, along with the initial learning profile elements can then be used to design learning analytics and personalisation goals that will provide richer and more comprehensive for the main stakeholder – the learner, the teacher and the university administrators and managers.

As explored in a related paper (Andre, Le & Webster, 2019), some of the barriers to the implementation of learning analytics systems in universities in Vietnam include the technological infrastructure and data sharing capabilities – which would be key elements in a top down management strategy to introduce learning analytics systems. To help overcomes these obstacles, it is proposed to prototype a bottom up unit or module based implementation using the free open source software and learning management system Moodle. Later versions of Moodle have learning analytics features which can provide feedback on the many learning and learning support activities and attributes of the environment. ISME at NEU has been using the Moodle learning management system since 2011.

Major advantages of Moodle include that it is free, open source software that is used by an estimated 80 million plus people world wide. “Free” does no mean lacking in quality. The UK Open University, the largest university in the country with 170,000 students has been a pioneer in developing and promoting online, distance and self regulated independent learning over the past 50 years. About 15 years ago the university carried out a comparative cost-benefit analysis of Moodle, Blackboard and other major learning management systems. They selected and implemented Moodle, a decision supported by the findings of a later comparative study by a Malaysian Universit (Subramanian et al, 2013).

The expanded learning profile will be developed with reference to more recent models which reflect an expanded view of the factors and components affecting student learning. One such model (Kurczewska et al, 2017) is shown below. The use of this model can introduces additional important factors such as motivation and conation into the complex process that is modern day student learning.

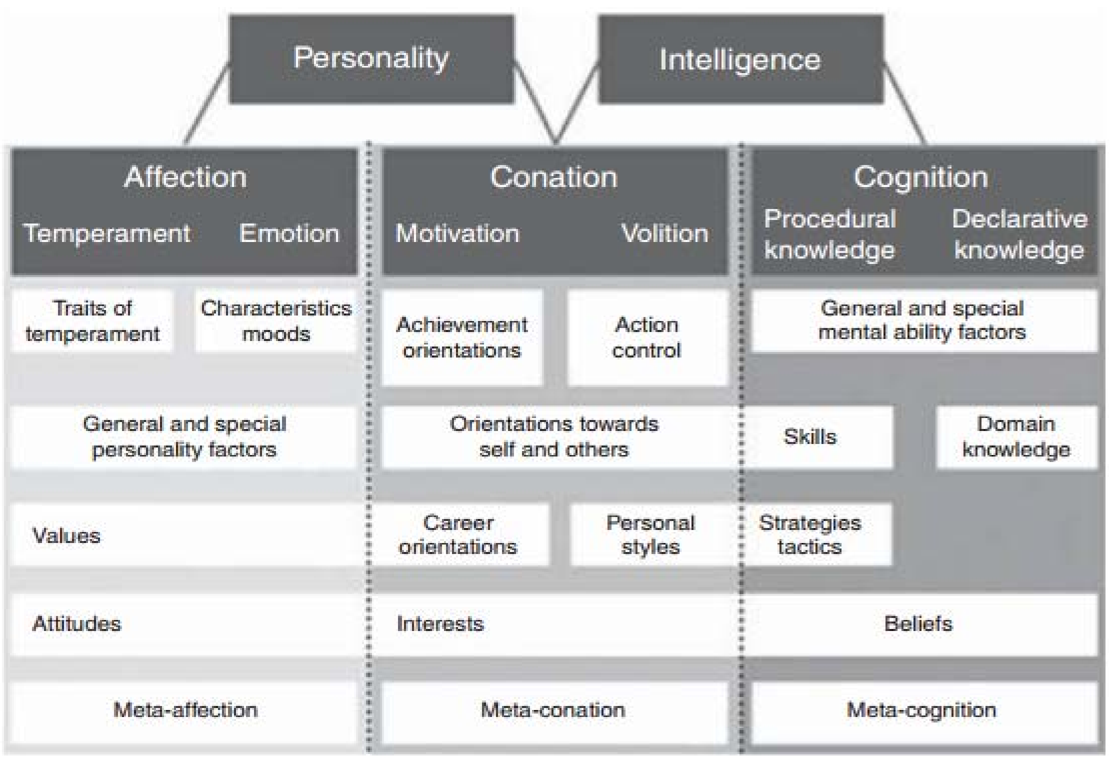

Figure N. Constructs and meta-constructs of personality and intelligence (Kurczewska et al, 2017)

This is especially important given the increase in student numbers in many countries and the resultant increase in the diversity of diversity in the social, economic and educational backgrounds of university students.

Although many of these factors were addressed using the original learning profile (especially Entwistle’s ASSIST with it 3 main scales – Deep, Strategic, Surface/Apathetic learning – and thirteen sub-scales), the explicit labelling of the Motivation, Conation and Cognition sub-elements encourages a rethinking and expansion of the learning profile construct.. A key process will them be to use PERLA’s stages of the personalized learning activity cycle to generate indicators for the Moodle based module.

4.Interventions still necessary – design is the key activity.

In a talk in the May 2019 about how to use learning analytics in Moodle, the speaker (Scapin, 2019) pointed out that most of the data and learning analytics applications is generated by the learning management system itself. It consists of regular information such as numbers of logins, participation in learning activities, time spent interacting with peers, forums and other resources online or otherwise, plus of course grades.

Scapin (2019) also pointed out that the data provided by tracking systems is not intelligent in and of itself. It is the interpretation provided by the skilled analyst (hopefully trained teachers in future) that provides a useful feedback for the students, managers and teachers. For this silver care the data mining should provide suitable visualisations and as the business area has many years of providing such visualisations it is to be hoped that they can be transferred to the educational arena.

Currently the learning analytics outputs cannot automatically improve instruction. The outputs and visualisations can help to identify areas for improvement, but the interventions of the students, learning support groups, tutors and other involved personnel are needed to design and implement activities that can help the attainment the improved learning outcomes. Consequently, the overall systems design and the design of the learning support elements that will interface with the learning analytic sub-system outputs will be a key feature of a successfully implemented module. As educational systems designers of many years experience, we believe that the theoretical framework provided by PERLA and the practical experience provided by RAPAL can be used to provide a suitable Moodle based platform that integrates the best features of learning analytics feedback with powerful tools based on advances in learning science.

5. Conclusions: "*Let's not forget: Learning analytics are about learning.*"(Gasevic et al, 2015)

Learning analytics are indeed about learning, and from a variety of participant stakeholders perspectives (students, tutors, administration, technical support, management). But they are essentially about learning and improving learning.

This paper has discussed the possible impacts of the Fourth Industrial Revolution and applying digital technologies and big data analytics to higher education in Vietnam. It has argued that it is necessary for us to consider the learning science side of individual learning in order to complement the undeniable advantages that learning analytics will bring to higher education. Observing the experiences of other ASEAN members, such as Singapore, in the development and implementation of learning analytics through learning management systems such as Blackboard and Moodle is likely to be a particularly productive approach. The open-source approach, cost, widespread learning support community and modular features of Moodle provide particular advantages for the education sector in Vietnam.

A couple of years ago, the following comment was made by two experienced educational technologist:

"A learning analytics project within an institution is not only a research/development activity or a technological issue, but also an organisational issue." (Boyer & Bonnin, 2016).

It can be argued that, while this astute comment certainly holds for universities in this country, the implications are much bigger for Vietnam. The adoption of the bottom-up, module implemented learning analytics and learning support systems approach outlined above could help the higher education sector as a whole to overcome the infrastructure and data sharing barriers that exist. It is hoped that organisational, regional and national leaders in higher education will recognize and embrace this opportunity.

References

Andre, J., Le, T.K. & Webster, R., (2018), Academic Leadership and Learning Analytics in Higher Education in Vietnam. *Proceedings: SEAMEO International Conference: Leadership and Management in Higher Education: Driving Change with Global Trends*. Ho Chi Minh City, July 4-5, 2019.

Andre, J. & Webster, R., (2018), Leveraging Analytics in Vietnam. Proceedings 1st International Conference on Contemporary Issues in Economics, Management and Business, National Economics University, Hanoi, November 2018

Andre, J. & Webster, R., (2017), *Fostering Entrepreneurial and Collaborative Skills in Business Management Students in Vietnam*. Presented at International Conference on Economics and Business Management, Foreign Trade University, Hanoi, November 2017

Boyer, A. & Bonnin, G. (2016). *Higher Education and the Revolution of Learning*

Analytics. International Council for Open and Distance Education.

Chatti, M. A. 2010. *Personalization in Technology Enhanced Learning: A Social Software Perspective*, Aachen, Shaker Verlag.

Chatti, M. A. & Muslim, A. (2019). The PERLA Framework: Blending Personalization and Learning Analytics. *International Review of Research in Open and Distributed Learning*, v20n1

Gašević, D., Dawson, S., Siemens, G. (2015). Let's not forget: Learning analytics are about learning, *TechTrends*. v59.1, 64–71.

Goswami, A., Menon, J. & Fink, A. M. 2017. ASEAN at 50: What does the Fourth Industrial Revolution mean for ASEAN Economic Integration? Asia Development Bank. (18/6/19)

Hoh, M.C., Cho, W.O. & Siew, P.H. (2011). *Implementation of LMS among Private Higher Learning Institutions in Malaysia.* Universiti Tunku Abdul Rahman, Malaysia.

Jonassen, D.H. and B.L. Grabowski, (1993) *Handbook of Individual Differences , Learning , and Instruction.* Hillsdale, N.J.: Lawrence Erlbaum Assocs,.

School of Management, Massachusetts Institute of Technology.

Kurczewska, A., Kyro, P., Lagus, K., Kohonen, O. & Lindh-Knuutila, T. 2017. The interplay between cognitive, conative, and affective constructs along the entrepreneurial learning process. *Education + Training,* 60**,** 891-908.

Likens, S. (2018) *Emerging trends and business opportunities from big data analytics*. Online at: https://www.pwccn.com/en/services/consulting/publications/emerging-trends-and-business-opportunities-from-big-data-analytics.html

Lim, C. P. & Tinio, V. L. (eds.) 2018. *Learning analytics for the global south*. , Quezon City, Philippines: : Foundation for Information Technology Education and Development.

Maine, W. S. (2011) . "Learn, Unlearn, Relearn". Singapore Public Services Division, https://www.psd.gov.sg/challenge/people/cuppa/learn-unlearn-relearn (Accessed 10/6/19)

Mwalumbwe, I. & Mtebe, J. S. 2017. Using Learning Analytics to Predict Students' Performance in Moodle Learning Management System: A Case of Mbeya University of Science and Technology. *The Electronic Journal of Information Systems in Developing Countries,* 79**,** 1-13.

Norman, D. (2013). The *Design of Everyday Things* (Revised and expanded edition). New York: Basic Books.

NTU (2018) Blackboard Analytics: Learning Analytics for Faculty and Students. http://www.ntu.edu.sg/cits/lsa/BlackboardAnalytics/Pages/default.aspx

Reyes, C. T. (2018). Developing a student support system through learning analytics for undergraduates at the University of the Philippines Open University. Quezon City, Philippines: Foundation for Information Technology Education and Development

Ross, J. (2018). Lifelong learning vital for Singapore to avert 'bleak' future. *Times Higher Education,* London, Sept. 2018.

Siemens, G., (2018) *The future of learning and knowledge: Human and artificial intelligence.* Keynote: LACOL Workshop. Los Angeles, May 31 2018.

Subramanian, P., Zainuddin, N., Alatawi, S., Javabdeh, T. & Hussin, A. R. C. 2013. A Study of Comparison between Moodle and Blackboard based on Case Studies for Better LMS. *Journal of Information Research and Innovation.*

Thille, C. & Zimmaro, D. (2017). Incorporating learning analytics in the classroom. In Zilvinskis, J. & Borden, V. (Eds.). *New Directions for Higher Education*. Hoboken, NJ: Wiley.

Thille, C. (2016). What the science of learning indicates we should do differently. In Otte, G. Goldstein, M. (Eds.), *Change We Must: Deciding the Future of Higher Education*. New York, NY.

Vietnam News (2018) WEF ASEAN 2018: PM Nguyễn Xuân Phúc welcomes Singaporean counterpart. (accessed 2/6/19)

Webster, .R. (2005). *A reflective and participatory approach to the design of personalised learning environments*. Unpublished PhD Thesis, Lancaster, Lancaster University.

Webster, R. (2008) RAPAL: A Reflective and Participatory Methodology for E-Learning and Lifelong Learning. In F.J. Garcia (Ed.), *Advances in E-Learning: Experiences and Methodologies*. Hershey, PA: Idea Group Publishing.

Webster, R. (2009) *Personalizing Learning: Reflective and Participatory Design for Autonomous Learning*. Vdm Verlag.

Webster**,** R. & Andre, J., (2018) , Flexible Student Alignment for Self-Directed Learning and 21Century Skills Development. *Proceedings, SEAMEO International Conference: Leadership and Management in Higher Education in a Globalized World: Innovations and Best Practices*. Ho Ch Minh City, 5-6 July 2018.

Wong, J., Baars, M., De Koning, B. B., Van Der Zee, T., Davis, D., Khalil, M., Houben, G.-J. & Paas, F. (2019). Educational Theories and Learning Analytics: From Data to Knowledge. In: Ifenthaler, D., Mah, D. & Yau, J. (eds.) (2019) *Utilizing Learning Analytics to Support Study Success* Cham: Springer.

Authors' biographies

Ray Webster is Head of Professional Development at the International School of Management and Economics, National Economics University, Hanoi. He has worked for many years in the fields of information systems and education in countries such as the UK, Malaysia, Australia and Vietnam. He received his MSc in Intelligent Systems from Brunel University, UK and his Ph.D. in Educational Research from the University of Lancaster , UK. His main research interests are self-directed learning, metacognition and technology-based learning in higher education, with a particular focus on the combined uses of learning analytics and learning science methodologies to enhance student learning. He can be contacted via raywebster@isneu.org

John Andre is an American entrepreneur and educator with a strong track record of success in both fields. He founded several companies, including Montgomery Software, which made its name in training and consulting for corporate clients around the world. He is currently a senior lecturer for National Economics University in Hanoi, Vietnam and teaches business management, finance, personal development, and soft skills. Mr. Andre's current research areas include learning analytics, learning science, and student motivation. His recent consulting and training clients include the Vietnamese government, state-owned enterprises, and private firms across the country. He can be contacted via john.andre@isneu.org

Trinh Thi Thu Giang is Vice Dean at International School of Management and Economics, National Economics University. She received her MBA degree from Washington State University and is currently pursuing her doctoral studies at NEU. With more than 15 years experience of developing international programs in partnership with UK and US universities, she is very keen at improving students learning experiences in Vietnam as well as matching their learning outcomes with international standards. Her main research interests are student engagement, learners' behaviors and higher education quality assurance. She can be contacted via trinh.giang@isneu.org