Interdisciplinary Journal of Virtual Learning in Medical Sciences

Original Article

Investigation on the Role of Learning Theory in Learning Analytics

Seyyed Kazem Banihashem[1*], PhD candidate; Khadijeh Aliabadi[1], PhD; Saeid Pourroostaei Ardakani[1], PhD; Mohammad Reza Nili AhmadAbadi[1], PhD; Ali Delavar[2], PhD

[1]*Department of Educational Technology, Faculty of Psychology and Educational Sciences, Allameh Tabataba'i University, Tehran, Iran*
[2]*Department of Assessment and Measurement, Faculty of Psychology and Educational Sciences, Allameh Tabataba'i University, Tehran, Iran*

ABSTRACT

Background: Studies have shown that there is a gap between theory and practice in the use of learning analytics in educational settings. Some researchers attribute this gap to not taking learning theories into consideration in the use of learning analytics in educational contexts. This study was conducted to address the role of learning theory in applying learning analytics in educational contexts.

Methods: This is a qualitative study and the study design is content analysis. Thematic analysis was used as the research method. Data for this study was collected through an interview with 14 experts in the fields of learning analytics and learning theory who were selected purposefully. Theoretical saturation method was used to determine the sample size. Content analysis techniques were used to analyze data and content validity index (CVI) and Cohen's kappa coefficient were performed to measure the validity and reliability of the findings.

Results: Data analysis was performed to identify three main roles for learning theory in learning analytics including underpinning role, guiding role, and sense-making role.

Conclusion: The results suggest that first, learning theory should underlie learning analytics (*where* to begin). Second, application of learning analytics in educational settings should be guided by learning theory (*what* and *how* to do), and third, learning analytics' reports should be interpreted based on the learning theory implications for education (answer to question *why*).

Keywords: Learning theory, Learning analytics, Thematic analysis

**Corresponding author:*
Seyyed Kazem Banihashem, PhD candidate;
Department of Educational Technology, Faculty of Psychology and Educational Sciences, Allameh Tabataba'i University, Tehran, Iran
Email: k.banihashem@atu.ac.ir

Please cite this paper as:
Banihashem SK, Aliabadi K, Pourroostaei Ardakani S, Nili AhmadAbadi MR, Delavar A. Investigation on the Role of Learning Theory in Learning Analytics. Interdiscip J Virtual Learn Med Sci. 2019;10(4):14-27.doi:10.30476/IJVLMS.2019.84294.1001.

Received: 07-10-2019
Revised: 27-11-2019
Accepted: 30-11-2019

Introduction

In the digital age, we come across a new generation that is called "*digital natives*" (1). Technology Enhanced Learning (TEL) is a key concept for the education of digital natives, and thanks to the technology, we are now able more than ever to track data about learners and teachers in learning contexts. Data plays a key role in today's education and some declare data-driven approach in education (2-4). Siemens and Long (5) point out that big data and analytics are two critical keywords of the future education. In view of the ever-growing attention to data and analytics, the field of *Learning Analytics* (LA) was born in 2011 to measure, collect, analyze and report data about learners and their context for the purpose of understanding and optimizing learning and the environments in which it occurs (5). Studies have demonstrated that learning analytics could offer noticeable advantages and useful insights to boost education. For example, learning analytics could inform teachers about learning process, identify students at risk of failure, increase students' retention rate, provide real time feedback for teachers and learners, identify students' learning habits, improve learning design, provide evidence-based decisions, enhance students' engagement, provide insights about students' interaction and social networks, and improve personalized learning (6-13). But, this promising and newborn field of study suffers from a gap between its theory and practice (14). Siemens (13) and Knight, Buckingham Shum, & Littleton (15) mention the threat of technological and mechanical determinism in the use of learning analytics tools in educational settings. Studies have shown that educational innovations would not be introduced successfully by simply providing access to new tools (16-18). New technologies in education would be used marginally if there is no plan to shift patterns of teaching and learning activities. Introducing new technologies in education is in need of being passed through the filter of educational foundations. Gašević et al (19) state that general learning analytics models have less reliable academic success predictions, while course-specific learning analytics models could offer more reliable results. It means one learning analytics model might not fit all learning contexts.

As a multidisciplinary field of study, learning analytics borrows ideas from different areas such as statistics, computer science, machine learning, pedagogy, business intelligence and learning science (8). But, the joining point of all these areas in learning analytics is the concept of *learning*. Learning analytics is about learning (20) and the purpose of learning analytics is to optimize and improve learning (5). We need to understand what learning means in different contexts to appropriately use learning analytics (20). Also, learning theory plays an underlying role in teaching and learning process, because different learning theories have their own specific educational implications (21). For example, learning and teaching process based on the connectivism theory is different compared to cognitivist learning theory. From a connectivist perspective, networks and nodes are the two key factors (22, 23) while in cognitivism, other factors such as memory (coding, encoding, and retrieval), previous knowledge, mental structure, and schema are playing important roles (24). Or behaviorists believe that external motivations like rewards, and reinforcements are the factors that influence learning, and consider thoughts, perceptions, memory, or consciousness as a black box which cannot be measured or observed (25-27) while constructivists consider learning as a personal construction of knowledge (28, 29) and mention engagement, collaboration, problem solving, social and cultural settings as factors that influence learning (30, 31).

This is apparently the reason why learning theories are important in potentially filling the gap between theory and practice in the use of learning analytics in educational settings. A clear understanding of learning could help the users of learning analytics to know what exactly they should be looking to capture, analyze and report and how these findings should be interpreted to properly inform learning analytics stakeholders such as teachers and learners. This study takes learning theory in general into account, and tries to bridge the gap between theory and practice in learning analytics. Based on the above-mentioned points, this study aims to answer the following question:

What is the role of learning theory in applying learning analytics in educational contexts?

Methods

This is a qualitative study in which the design of the study was content analysis, and thematic analysis was used as the research method. According to Braun, Clarke, Hayfield & Terry (32), "thematic analysis is a method for systematically identifying, organizing and offering insights into patterns of meaning (theme) across data set" (p. 57). Thematic analysis consists of six phases as follows: (1) familiarizing with data, (2) generating initial codes, (3) searching for themes, (4) reviewing potential themes, (5) defining and naming themes, and (6) producing the report (33, 34). In the phase one, the researchers started reading and re-reading the data in order to become familiar with them and to know what should be focused on. In phase two, the researchers started with initial coding to identify where and how patterns occur. In phase three, the researchers tried to combine codes and develop themes. In this phase, it was tried to understand which code matches with the other one conceptually. In phase four, the researchers focused to understand how these themes support data and to make sure that there is no missing data. In phase five, the researchers mentioned which data are captured to support these themes and explained why this is interesting, as indicated by the sample codes in the results section. Finally, in phase six, the researchers provided a thick description of the results.

Participants

In this study, we interviewed 14 experts in the field of learning analytics and learning theory. Purposeful sampling method was used to select participants and the strategy to select these experts was based on their theoretical and research relevance. The reason why 14 experts were interviewed was "theoretical saturation", which means that data collection process continued until no new data was left to be collected. In other words, data satisfaction was met. Demographic information of the participants is reported in Table 1.

Data Collection

Data were collected in four forms: (1) in person interview, (2) skype interview, (3) email, and (4) paper-based questionnaire. To collect data, at first, interview question was developed based on the research question. Four participants were interviewed in person and data were collected in both visual and audial forms. Three out of fourteen participants were interviewed through skype and their responses were collected in both visual and audial forms. Five participants preferred to fill the paper-based questionnaire and one participant did the email interview. Interview question was unstructured, open-ended, and was mainly based on two concepts including learning theory and learning analytics (Table 2).

Data Analysis

To analyze data, three open coding, axial coding, and selective coding processes were followed. These processes were first introduced by Strauss & Corbin (35) based on the Glazer & Strauss (36) idea of grounded theory. Open coding helps researchers identify, name, categorize, and describe the themes that exist in the data set. Open coding is called "line-by-line coding" which is the first step to recognize and build concepts (37, 38). In the axial coding, codes are refined, related to each other, and combined to develop categories of greater concepts. Axial coding prepares a coding template to merge and organize data into more coherent, hierarchically structured categories and subcategories that add nuance and dimension to emergent concepts and their potential relationship to other elements (39). Selective coding focuses on the process of

Table 1: Demographic information of the participants

		F	Pct
Gender	Female	5	%35
	Male	9	%65
	Total	14	%100
Country	Canada	7	%50
	USA	1	%7
	Australia	2	%14
	UK	2	%14
	Iran	1	%7
	Netherland	1	%7
	Total	14	%100
Degree	M.A	2	%14
	PhD	12	%86
	Total	14	%100
Institution	University of British Columbia	5	%37
	Simon Frazer University	2	%14
	Open University	2	%14
	University of Michigan	1	%7
	University of Technology Sydney	1	%7
	University of South Australia	1	%7
	University of Amsterdam	1	%7
	Virtual University of Medical Sciences	1	%7
	Total	14	%100
Position	Faculty member	11	%79
	Learning designer	1	%7
	Research analyst	1	%7
	LA expert	1	%7
	Total	14	%100

Table 2: Interview question

Question
What do you think about the role of learning theories [behaviorism, cognitivism, constructivism, and connectivism] in learning analytics?

selecting one category as the core category, and linking all other categories to that category (40). Data were coded, analyzed and visualized by qualitative data analysis software (MAXQDA, Version 2018). To examine the validity of the coding results, content validity index (CVI) was performed, and to measure the reliability of the results, Cohen's kappa coefficient was used. Results for the CVI, and Cohen's kappa coefficient are presented in the next section (Tables 3 and 4).

Results

Demographic information of the participants is presented in Table 1.

According to the demographic information provided in Table 1, most of the participants were male (65 percent) and faculty member (79 percent). About 50 percent of the participants were from Canada and 37 percent of the experts participated from the University of British Columbia. In the next section, results for the research question are provided.

What is the role of learning theory in applying learning analytics in educational contexts?

Data analysis for the research question showed that three main roles can be identified for learning theory in the application of learning analytics which are underpinning role, guiding role, and sense-making role. The results are presented in Figure 1 and Table 5.

Table 3: Content validity index (CVI) results

Category	Subcategory	Number of experts agree	Number of experts do not agree	CVI
Underpinning	Important but not consider in current initiatives	8	8	0.50
	Learning theory underlies learning analytics	14	2	0.87
	Different theories require different analytics	13	3	0.81
	Theory underlies design and design underlies analytics	13	3	0.81
	Theory tells where are we coming from	13	3	0.81
	Theory underlies design	14	2	0.87
	Theory underlies education questions	14	2	0.87
	Theory underlies teaching	14	2	0.87
	Learning theories underpin sense-making	13	3	0.81
	Theory as a part of the cycle	13	3	0.81
	Top to down	14	2	0.87
Guiding	Theory guides analytics	13	3	0.81
	Data inform theories	13	3	0.81
	How data is collected	10	6	0.62
	Theory says what analytics to focus on	14	2	0.87
	Analytics are guided by theory	14	2	0.87
	Theory helps to know what we need to collect	13	3	0.81
	Theories inform teaching	13	3	0.81
	One percent of work goes to theory in data analytics	13	3	0.81
	Data inform teaching and learning	14	2	0.87
	Theory as a lens of viewpoint	14	2	0.87
	Theory decides how to analyze data	14	2	0.87
	How data is analyzed	13	3	
Sense-making	Theory explains learning, behavior, experiences, outcomes	14	2	0.87
	Tango	9	7	0.56
	Theory in sense-making is crucial	13	3	0.81
	Data transforms into knowledge	14	2	0.87
	Learning context matters in sense-making and transformation	13	3	0.81
	Data interpretation	14	2	0.87
	Understand data	14	2	0.87
	Theory answers questions	14	2	0.87
	Data presentation articulated in theory	13	3	0.81
	Theory in empirically based interventions	11	2	0.68
	Theory helps practice	14	2	0.87
	Data into knowledge	13	3	0.81

Table 4: Cohen's kappa coefficient result

	Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement Kappa	0.642	0.110	6.685	0.001
N of Valid Cases	29			

a. Not assuming the null hypothesis. b. Using the asympotic standard error assuming the null hypothesis

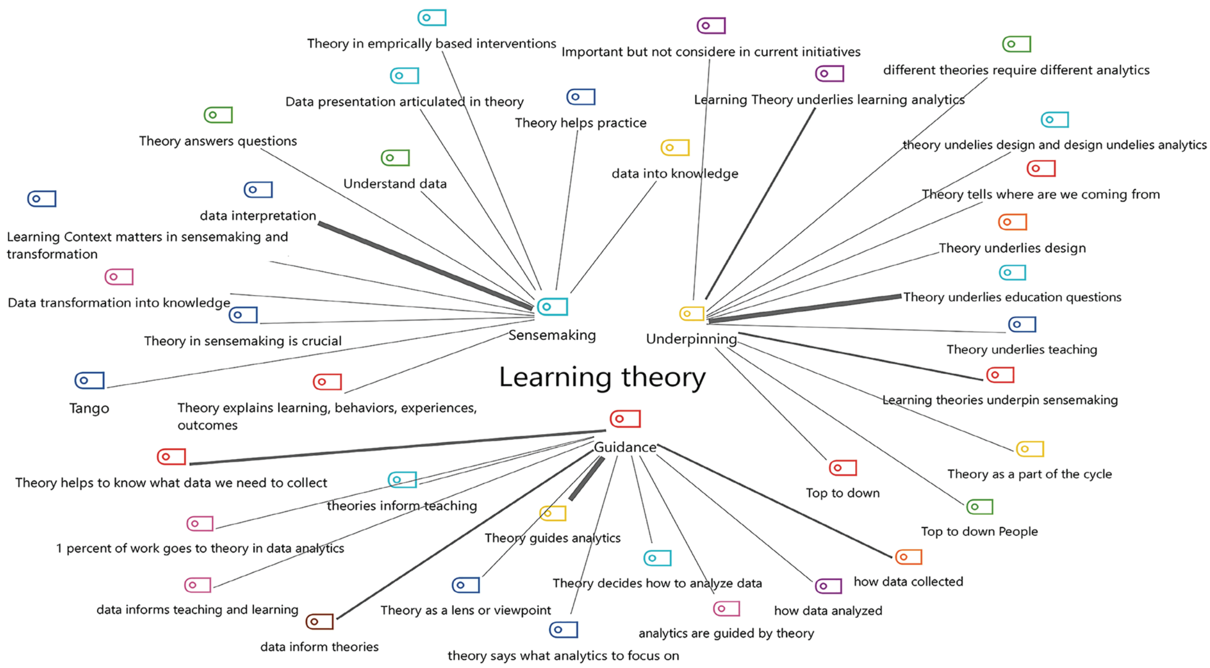

Figure 1: Roles identified for learning theory in learning analytics

As it is shown in Figure 1, three main categories were extracted from data in which category for the underpinning role includes 11 subcategories, the guiding category consists of 12 subcategories, and category for the sense-making contains 12 subcategories. In Table 5, the results are presented with more details. It should be noted that sample codes in the Table 5 are presented anonymously with a specific code for each interviewee.

According to Table 5, in the guiding category, two subcategories have received more attentions among the interviewees which are "theory guides analytics" and "theory helps to know what we need to collect". While, in the underpinning category, three subcategories including "theory underlies education questions", "learning theories underpin sense-making", and "learning theory underlies learning analytics" have been more frequently mentioned by the interviewees. In the underpinning category, it is found that "data presentation articulated in theory", "understand data", and "data transforms into knowledge" are highly important compared to other subcategories based on their frequency. In the following section, the three main categories are explained.

Underpinning: In the underpinning role, learning theory underlies analytics. Learning theory gives insights about how people learn and there is no point in learning analytics unless it is related to an understanding of how people learn. "…T*o my mind, there's no point in learning analytics unless they are related to an understanding of how people learn*" (12QRF). Theoretical foundations would help users of learning analytics to know where they are coming from. "…*We have to be very clear where we are coming from, what is the theoretical point of departure for us and whatever data we are getting*" (8HMH). It is theory that underpins sense-making of data. "*So, the answer to this question is that I think theory should underpin the reasoning about how to use data to improve learning experiences*" (2BAP). Learning analytics would not be understood and used effectively if it was not built on the theory and the framework based on which the course is designed. "…*They are underlying theory in design and having connections to the data that they might need or want*" (6FLM). This is a top-to-bottom view, where it begins with theory and then one looks for data that can inform the theory, "…*And then there are people who are more top to down which starts with the theory and look for data that*

Table 5: Coding results for learning theory and learning analytics

Category	Subcategory	Frequency	Sample Code
Guiding	Theory guides analytics	6	*"I think we need to be guided much more strongly by underlying concepts as they are defined in the learning science."* (8HMH)
	Data inform theories	3	*"I think it is really a great opportunity to investigate in those theories and think about ways on the new data the helps us understand the theory."* (13PST)
	How data is collected	3	*"The data collected are also driven by that theory (a scale from 0 to 100 in both dimensions)."* (2BAP)
	Theory says what analytics to focus on	2	*"Theory helps to know what analytics to focus on."* (7JLL)
	Analytics are guided by theory	2	*"Learning analytics add information about how a design is "used" (are learners doing what the design describes or deviating?) and what outcomes arise (are learners achieving objectives, feeling good or oppressed when they achieve objectives). What to do with analytics about a design's use and outcomes should be guided by theory."* (11NPW)
	Theory helps to know what we need to collect	4	*"I think learning theory could help the users of learning analytics decide which types of data they wish to collect."* (7JLL)
	Theories inform teaching	1	*"So teaching produces instruction. Instruction feeds into learning. Learning creates data. Data inform theories and theories inform teaching."* (5EIR)
	One percent of work goes to theory in data analytics	1	*"So that probably 80 percent of the work. We just have data and we calculated correlations and we did graphs and nothing happened with us. And 19 percent of the time we do that. We use the data to inform teaching and just 1 percent that actually goes to theories."* (5EIR)
	Data inform teaching and learning	1	*"With that being said, I believe that learning analytics are valuable because they can tell us about students and their learning experiences, which can inform teaching and learning practice."* (12QSS)
	Theory as a lens of viewpoint	1	*"I see it more as pedagogical viewpoint or lens, much in the way we think about problem based learning or situated learning."* (14QSS)
	Theory decides how to analyze data	1	*"…how can that data be analyzed in order to understand those questions."* (7JLL)
	How data is analyzed	1	*"I think that knowledge of data analysis techniques and how data are interpreted would be more meaningful for formulating interventions than knowledge of learning theories."* (14QSS)
Under-pinning	Important but not consider in current initiatives	1	*"I think the role of learning theories in Learning Analytics is very important, but at the same time, not taken into account properly in current initiatives."* (2BAP)
	Learning theory underlies learning analytics	3	*"To my mind, there's no point in learning analytics unless they are related to an understanding of how people learn."* (12QRF)
	Different theories require different analytics	2	*"Thus social network analysis could be useful for connectivist courses but not those which don't use forums or other ways of facilitating student interaction with each other."* (10MNS)

	Theory underlies design and design underlies analytics	1	*"Arguably you cannot be effective in using learning analytics unless you understand the framework which the course designers built on."* (10MNS)
	Theory tells where are we coming from	1	*"We have to be very clear where we are coming from, what is the theoretical point of departure for us and whatever data we are getting."* (8HMH)
	Theory underlies design	2	*"…they are underlying theory in design and having connects to the data that they might need or want."* (6FLM)
	Theory underlies education questions	6	*"Well I think learning theory could help the users of learning analytics decide which types of data they wish to collect to answer which kind of questions from a theoretical basis."* (7JLL)
	Theory underlies teaching	1	*"…theory underlying their teaching or design."* (6FLM)
	Learning theories underpin sense-making	3	*"So, the answer to this question is that I think theory should underpin the reasoning about how to use data to improve learning experiences."* (2BAP)
	Theory as a part of the cycle	1	*"I think theory should be part of the cycle."* (5EIR)
	Top to down	1	*"…and then there are people who are more top to down which starts with the theory and look for data that can inform the theory."* (13PST)
Sense-making	Theory explains learning, behavior, experiences, outcomes	1	*"So, I think that there are lots of theories about learning and it is important to understand those theories really to, narrowing to what someone should want to know about students learning, behaviors, experiences, outcomes, but also try to understand what has happened."* (7JLL)
	Tango	2	*"For me it is like a tango. In essence like without learning theory you can't understand data but also you can't understand learning theory without data. So, for me they're always dancing together, if you see what I am trying to say."* (3CBR)
	Theory in sense-making is crucial	1	*"…when processing the data collected from a learning experience, there is one step that typically referred as "sense-making" that is crucial."* (2BAP)
	Data transforms into knowledge	4	*"It needs to be processed and transformed into a format that is closer to knowledge."* (2BAP)
	Learning context matters in sense-making and transformation	1	*"These transformations or "sense-making" is a loosely defined term, but one of the most important aspects is that it is extremely dependent on the learning context."* (2BAP)
	Data interpretation	3	*"…and the interpretation is done under the umbrella of that theory."* (2BAP)
	Understand data	4	*"In essence like without learning theory you can't understand data but also you can't understand learning theory without data."* (3CBR)
	Theory answers questions	2	*"…what you really want to know, what are you trying to achieve."* (6FLM)

	Data presentation articulated in theory	6	*"Without that understanding of pedagogy, we are left with metrics, and we are much more likely to focus on what can easily be measured rather than on what we are trying to achieve by collecting, analyzing and presenting data."* (12QRF)
	Theory in empirically based interventions	2	*"Theories only become meaningful when empirically-based interventions (based on these theories) can be identified based upon existing data, but the link between data and learning should be pretty clear within the data."* (14QSS)
	Theory helps practice	2	*"I think it definitely needs more work on both sides to have better theory to understand and then see how it is tested in practice."* (9LNP)
	Data into knowledge	1	*"The data collected through technology mediation is not readily available to be used for analysis and prediction. It needs to be processed and transformed into a format that is closer to knowledge."* (2BAP)

can inform the theory" (13PST). Then, in the underpinning role, learning theory tends to help learning analytics applicants to know "*where*" to begin.

Guiding: Learning theory gives information about what learning means, how students learn, how they process information, and what factors could be important in teaching and learning process. As maintained by interviewees, "*what to do with analytics about a design's use and outcomes should be guided by theory*" (11NPW). "*I think we need to be guided much more strongly by underlying concepts as they are defined in the learning science*" (8HMH). "*The data collected are also driven by that theory*" (2BAP). "*I think learning theory could help the users of learning analytics to decide which types of data they wish to collect*" (7JLL). Learning theory guides learning analytics to effectively use data. Learning theory works as a pedagogical lens or viewpoint to understand what types of data are needed to be collected, how collected data should be analyzed, and to whom results should be reported. "*I see it more as pedagogical viewpoint or lens, much in the way we think about problem based learning or situated learning*" (14QSS). Then, it could be said that data collection and data analysis are driven by theory and that is theory which might tell us what analytics should focus on. "*Theory helps to know what analytics to focus on*" (7JLL). Learning theory guides and informs learning analytics to effectively and appropriately answer educational questions by informing learning analytics applicants to know what to collect and how to analyze. That is to say, in the guiding role, learning theory would help learning analytics to answer questions about "*what*" and "*how*".

Sense-making: It is theory that explains learning, behavior, experiences and outcomes and without learning theory, we cannot understand data. "*I think that there are lots of theories about learning and it is important to understand those theories really to, narrowing to what someone should want to know about students learning, behaviors, experiences, outcomes, but also try to understand what has happened*" (7JLL). "*In essence like without learning theory you can't understand data but also you can't understand learning theory without data. So, for me they're always dancing together, if you see what I am trying to say*" (3CBR). Data can be transformed into knowledge and wisdom if there is a theory behind that. "*The data collected through technology mediation is not readily available to be used for analysis and prediction. It needs to be processed and transformed into a format that is closer to knowledge*" (2BAP). Learning theory helps learning analytics users to interpret data appropriately. "*Without that understanding of pedagogy, we are left with metrics, and we are much more likely to focus on what can easily be measured rather than on what we are trying to achieve* *by collecting, analyzing and presenting data*" (12QRF). Learning theory helps to make sense of data and data interpretation is done under the umbrella of learning theory. "*…And the interpretation is done under the umbrella of that theory*" (2BAP). By theory behind analytics we could know why this data is collected, why this data is important, and why this is happening. It is envisioned that in the sense-making role, learning theory tends to help address questions about "*why*". In this role, learning theory could contribute in terms of understanding data and interpreting it appropriately.

Based on the above explanations, conceptual framework of the role of learning theory in the use of learning analytics in educational contexts are presented in Figure 2.

Figure 2 outlines that learning theory has three main roles in learning analytics in three steps which begin with the underpinning role, where it plays more a theoretical and foundational role by underlying analytics in the theory. Then it continues with the guiding role where it is practical and more about process than the results of learning, and finally in the third step, learning theory plays a sense-making role, where it helps analytics to have a better understanding and interpretation of the data reports and results.

Validity and Reliability

To validate content analysis results, CVI was performed. If the CVI score is above 0.79, then the content validity of the scale is confirmed. In other words, the minimum acceptable value for the CVI is 0.79. Results are presented in Table 3.

According to the results of the CVI in Table 3, in the underpinning category, the subcategory "important but not consider in current initiatives" did not meet the content validity criteria. In the guiding category, the subcategory "how data is collected" did not have the validity, and in the sense-making category, two subcategories including "tango", and "theory in empirically based interventions" were not validated by experts. The rest of the subcategories were validated.

To measure the reliability of the coding results, Cohen's kappa coefficient was performed. If the value of the kappa index is higher than 0.60, it means that the model is reliable. Result of the analysis is presented

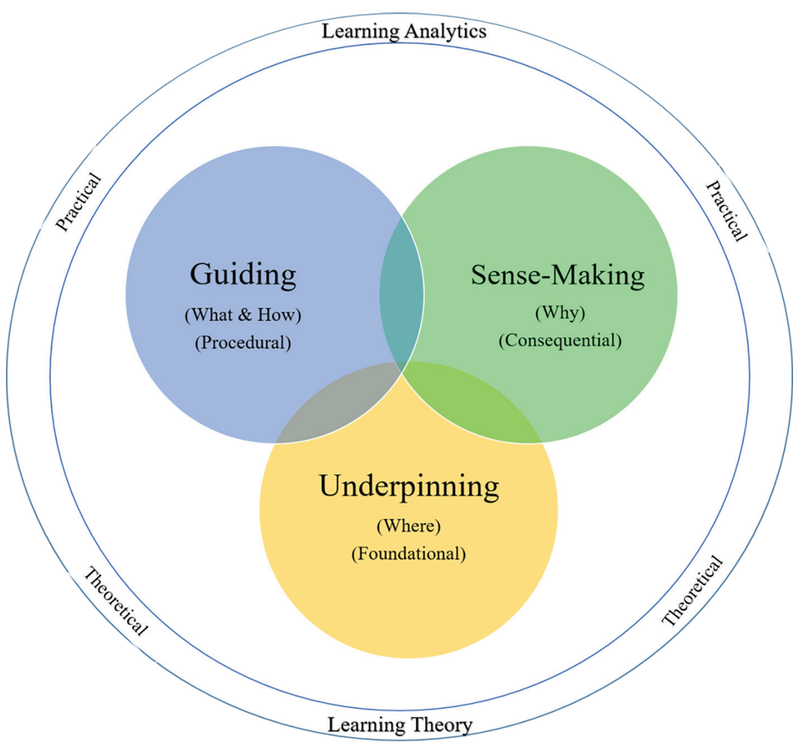

Figure 2: Conceptual framework of learning theory's role in learning analytics

in Table 4.

Based on the result shown in Table 4, the value of the test is higher than 0.60 and it is a significant number ($P<0.01$). Then, it can be said that the findings of the coding are reliable.

Discussion

The effective and successful use of learning analytics in educational contexts is highly dependent on taking theoretical foundations into consideration (8, 14, 18, 41). Without giving attention to theory, learning analytics applications could be threatened by technological determinism (13). Learning theory describes learning process and gives insights about how and why people learn (42, 43). Because of the importance of the learning theory in underlying teaching and learning process, this study was an initial attempt to explain the role of learning theory in learning analytics application as one of the main theoretical foundations in the teaching and learning process to decrease the threat of technological determinism and potentially bridge the gap between theory and practice in learning analytics. The results showed that learning theories could play three main roles in terms of applying learning analytics in educational contexts, which are the underpinning role, the guiding role, and the sense-making role. The results also showed that learning theory could inform learning analytics in three steps:)1) to inform teachers and learning analytics practitioners about where theoretically is better to begin the use of learning analytics in teaching and learning process,)2) to help learning analytics find out what types of data are better to be collected and how these data should be analyzed (a more considered as the procedural phase), and)3) to provide theoretical understanding of the learning analytics' reports to appropriately interpret findings and consequently make appropriate educational interventions. According to the findings, it is recommended to consider the teachers' perception of learning and the learning theory approach as a way to ensure an informed application of learning analytics across the whole process of teaching and learning.

Conclusion

To conclude, it is said that this study might make contributions to understand the importance of the word "*learning*" and the "*learning approach*" in learning analytics as it tends to be the core focus of any learning analytics activities. This qualitative study was an initial attempt at outlining the role of learning theory in the use of learning analytics in educational contexts, and further theoretical and empirical studies are needed.

Acknowledgment

We would like to express our deep gratitude to Dr. Leah P. Macfadyen from the University of British Columbia for her great support and we also thank all the participants who generously have shared their insights with us.

Declaration

No ethical issues were found. Participants have attended in this study willingly and data was presented anonymously. Participants were assured that their information will remain confidential.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author on request.

Funding

The authors declared that no financial supports were received for this study.

Authors' Contribution

S.K.B wrote the paper and collected data. K.A and S.P.A devised the study concept, designed the study, and supervised the research process. A.D and M.N.A contributed to the design, analysis of the study data and revised the manuscript.

Conflict of Interest

None declared.

References

1 Prensky M. Digital natives, digital immigrants part 1. On the horizon. 2001 Sep 1;9(5):1-6. https://doi.org/10.1108/10748120110424816
2 Zeide E. The structural consequences of big data-driven education. Big data. 2017 Jun 1;5(2):164-72. https://doi.org/10.1089/big.2016.0061
3 Cooper MM. Data-driven education research. Science. 2007 Aug 31;317(5842):1171-1183. https://doi.org/10.1126/science.317.5842.1171
4 Mokhtari K, Rosemary CA, Edwards PA. Making instructional decisions based on data: What, how, and why. The Reading Teacher. 2007 Dec 1;61(4):354-9. http://dx.doi.org/10.1598/RT.61.4.10
5 Siemens G, Long P. Penetrating the fog: Analytics in learning and education. EDUCAUSE review. 2011;46(5):30.
6 Lu OH, Huang JC, Huang AY, Yang SJ. Applying learning analytics for improving students engagement and learning outcomes in an MOOCs enabled collaborative programming course. Interactive Learning Environments. 2017 Feb 17;25(2):220-34. https://doi.org/10.1080/10494820.2016.1278391
7 Ifenthaler D. Are higher education institutions prepared for learning analytics?. TechTrends. 2017 Jul 1;61(4):366-71. http://dx.doi.org/10.1007/s11528-016-0154-0
8 Banihashem SK, Aliabadi K, Ardakani SP, Delaver A, Ahmadabadi MN. Learning analytics: A critical literature review. Interdisciplinary Journal of Virtual Learning in Medical Sciences. 2018; 9(2). https://dx.doi.org/10.5812/ijvlms.63024
9 Mah DK. Learning analytics and digital badges: Potential impact on student retention in higher education. Technology, Knowledge and Learning. 2016 Oct 1;21(3):285-305. https://doi.org/10.1007/s10758-016-9286-8
10 de Freitas S, Gibson D, Du Plessis C, Halloran P, Williams E, Ambrose M, Dunwell I, Arnab S. Foundations of dynamic learning analytics: Using university student data to increase retention. British Journal of Educational Technology. 2015 Nov;46(6):1175-88. https://doi.org/10.1111/bjet.12212
11 Conde MA, Hernandez-Garcia A. Learning analytics for educational decision making. Comput Hum Behav. 2015;47:1–3. https://doi.org/10.1016/j.chb.2014.12.034
12 Lawson C, Beer C, Rossi D, Moore T, Fleming J. Identification of ‘at risk’students using learning analytics: the ethical dilemmas of intervention strategies in a higher education institution. Educational Technology Research and Development. 2016 Oct 1;64(5):957-68. https://doi.org/10.1007/s11423-016-9459-0
13 Siemens G. Learning analytics: The emergence of a discipline. American Behavioral Scientist. 2013 Oct;57(10):1380-400. https://doi.org/10.1177%2F0002764213498851
14 Stewart C. Learning Analytics: Shifting from theory to practice. Journal on Empowering Teaching Excellence. 2017;1(1):10. https://doi.org/10.15142/T3G63W
15 Knight S, Shum SB, Littleton K. Epistemology, assessment, pedagogy: where learning meets analytics in the middle space. Journal of Learning Analytics. 2014 Aug 7;1(2):23-47. https://doi.org/10.18608/jla.2014.12.3
16 Wong J, Baars M, de Koning BB, van der Zee T, Davis D, Khalil M, Houben GJ, Paas F. Educational Theories and Learning Analytics: From Data to Knowledge. InUtilizing Learning Analytics to Support Study Success 2019 (pp. 3-25). Springer, Cham. https://doi.org/10.1007/978-3-319-64792-0_1
17 Ertmer PA. Addressing first-and second-order barriers to change: Strategies for technology integration. Educational technology research and development. 1999 Dec 1;47(4):47-61. https://doi.

org/10.1007/BF02299597
18 Wise AF. Designing pedagogical interventions to support student use of learning analytics. InProceedings of the fourth international conference on learning analytics and knowledge 2014 Mar 24 (pp. 203-211). ACM. http://dx.doi.org/10.1145/2567574.2567588
19 Gašević D, Dawson S, Rogers T, Gasevic D. Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. The Internet and Higher Education. 2016 Jan 1; 28:68-84. https://doi.org/10.1016/j.iheduc.2015.10.002
20 Gašević D, Dawson S, Siemens G. Let's not forget: Learning analytics are about learning. TechTrends. 2015 Jan 1;59(1):64-71. https://doi.org/10.1007/s11528-014-0822-x
21 Siemens G. Learning and knowing in networks: Changing roles for educators and designers. ITFORUM for Discussion. 2008 Jan 27; 27:1-26
22 Banihashem SK, Aliabadi K. Connectivism: implications for distance education. Interdisciplinary Journal of Virtual Learning in Medical Sciences. 2017;8(3). https://dx.doi.org/10.5812/ijvlms.10030
23 Goldie JG. Connectivism: A knowledge learning theory for the digital age?. Medical teacher. 2016 Oct 2;38(10):1064-9. https://doi.org/10.3109/0142159X.2016.1173661
24 Tennyson RD, Rasch M. Linking cognitive learning theory to instructional prescriptions. Instructional Science. 1988 Dec 1;17(4):369-85. https://doi.org/10.1007/BF00056222
25 Siemens, G. Connectivism. A learning theory for the digital age. International Journal of Instructional Technology and Distance Learning, 2005;2(1).
26 Akdeniz C. Instructional Process and Concepts in Theory and Practice. Singapore: Springer; 2016.
27 Bell F. Connectivism: Its place in theory-informed research and innovation in technology-enabled learning. The International Review of Research in Open and Distributed Learning. 2011 Mar 25;12(3):98-118. http://usir.salford.ac.uk/13064/
28 Mergel, B. Instructional design and learning theory. University of Saskatchewan. 1998. https://etad.usask.ca/802papers/mergel/mergel.pdf
29 Ertmer PA, Newby TJ. Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. Performance improvement quarterly. 2013;26(2):43-71. https://doi.org/10.1002/piq.21143
30 Altun S, Büyükduman FI. Teacher and student beliefs on constructivist instructional design: A case study. Kuram ve Uygulamada Egitim Bilimleri. 2007;7(1):30.
31 Richardson V. Constructivist teaching and teacher education: Theory and practice. In Constructivist teacher education 2005 Aug 15 (pp. 13-24). Routledge. http://dx.doi.org/10.4324/9780203973684
32 Braun, V., Clarke, V., Hayfield, N., & Terry, G. Thematic analysis. Handbook of research methods in health social sciences, 2018;1-18. http://dx.doi.org/10.1191/1478088706qp063oa
33 Terry G, Hayfield N, Clarke V, Braun V. Thematic analysis. The Sage handbook of qualitative research in psychology. 2017 Mar 31:17-37.
34 Braun V, Clarke V. Using thematic analysis in psychology. Qualitative research in psychology. 2006 Jan 1;3(2):77-101. https://doi.org/10.1191/1478088706qp063oa
35 Strauss A, Corbin J. Basics of qualitative research. Sage publications; 1998.
36 Glaser B, Strauss AL. The discovery of grounded theory: Strategies for qualitative research. 1967;139.
37 Böhm A. Theoretical Coding: Text Analysis in Grounded Theory. In Flick U. Kardoff E. & Stenlkne I. (Eds). A Companion to Qualitative Research. 2004:270-275.

38 Maher C, Hadfield M, Hutchings M, de Eyto A. Ensuring rigor in qualitative data analysis: A design research approach to coding combining NVivo with traditional material methods. International Journal of Qualitative Methods. 2018 Jul 9;17(1):1609406918786362. https://doi.org/10.1177%2F1609406918786362
39 Scott C, Medaugh M. Axial Coding. The International Encyclopedia of Communication Research Methods. 2017 Apr 24:1-2. https://doi.org/10.1002/9781118901731.iecrm0012
40 Robrecht LC. Grounded theory: Evolving methods. Qualitative health research. 1995 May;5(2):169-77. https://doi.org/10.1177%2F104973239500500203
41 Koh E, Shibani A, Tan JP, Hong H. A pedagogical framework for learning analytics in collaborative inquiry tasks: An example from a teamwork competency awareness program. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge 2016 Apr 25 (pp. 74-83). ACM. https://doi.org/10.1145/2883851.2883914
42 Mezirow, J. Transformative learning theory. In Contemporary Theories of Learning. Routledge. 2018;114-128. https://doi.org/10.4324/9781315147277-8
43 Akers RL, Jennings WG. Social learning theory. The Handbook of Criminological Theory. 2015 Aug 25;4:230-40. https://doi.org/10.1002/9781118512449