Interaction Design and Architecture(s) Journal - IxD&A, N.55, 2022-23, pp. 9 - 33

Evaluating the Impact of FoLA^2 on Learning Analytics Knowledge Creation and Acceptance during the Co-Design of Learning Activities

Marcel Schmitz[1], Maren Scheffel[2], Roger Bemelmans[1], Hendrik Drachsler[3,4]

[1] Zuyd University of Applied Sciences, Nieuw Eyckholt 300, Heerlen, Netherlands.
[2] Ruhr University Bochum, Universitätsstraße 150, Bochum, Germany.
[3] Open University The Netherlands, Valkenburgerweg 177, Heerlen, Netherlands.
[4] DIPF Leibniz Institut, Rostocker Straße 6, Frankfurt, Germany

Abstract. Learning analytics offers opportunities to enhance the design of learning activities by providing information on the impact of different learning designs. Despite the availability of design methods that aim to facilitate the integration of learning analytics in learning design, there is a lack of research evaluating their effectiveness. This study aims to assess the effectiveness of the FoLA^2 method. Sixty participants utilized the FoLA^2 method to create fourteen learning activities in higher education settings. To measure the impact, participants completed a technology acceptance test both before and after each session. Additionally, the researchers analyzed audio recordings of the sessions using epistemic network analysis to gain insights into the discussions surrounding learning analytics and the design of enriched learning activities. The results of both the technology acceptance test and the epistemic network analysis indicated that the FoLA^2 method effectively supports the integration of learning analytics during the design of learning activities.

Keywords: Learning Analytics, Learning Design, Technology Acceptance Model, Epistemic Network Analysis, co-creation, learning activities.

1 Introduction

The use of learning analytics and learning design has been gaining increasing attention in education. Researchers such as Law et al. [1], Pishtari et al. [2], and Banihashem et al. [3] have explored the connection between these two areas. They have demonstrated their potential to improve student engagement and self-regulation. Nguyen et al. [4] and Kelt et al. [5] have also highlighted the role of learning analytics (LA) in informing Learning Design (LD) in online education. In the special issue on `Learning Design and Learning Analytics for the Journal of Learning Analytics, Macfadyen, Lockyer, and Rienties collect several examples of LA-supported LDs [6]. In the past decade, most examples that address the LA-LD connection have been situated in the online education sector [7]. Face-to-face education examples are scarce. Several researchers report on instruments to facilitate teachers and students co-designing and implementing LA in LD. Examples are Gruber and Glahn [8], who extend their work on LD-Cards in workshops with LA elements. Alvarez et al. [9] introduced LA-Deck to support the co-design of analytics and visualization. Vezolli et al. [10] use general co-creation tools like the D.Stanford design tools [11]. Complementing these previous efforts, the FoLA^2 method enables teachers, students, and advisors to co-design LA-supported learning activities.

In the field of LA, the evaluation of design methods through usage studies is relatively scarce, despite the availability of numerous methods mentioned at the start of the introduction. To address this gap, this study focuses on evaluating the use of the FoLA^2 design method in practical settings. The primary objective of this evaluation study is to investigate whether the implementation of FoLA^2 contributes to the enhancement of LA's technology acceptance. Additionally, our study aims to provide insights into the collaborative efforts of various stakeholders in creating LA-supported learning activities and their discussions surrounding LA during the process. By examining the impact of FoLA^2 implementation on technology acceptance of LA, we contribute to the existing knowledge base by offering empirical evidence on the effectiveness of this particular method. Furthermore, our research sheds light on the practical aspects of utilizing FoLA^2, illustrating the engagement and perspectives of different stakeholders involved in designing and implementing LA-supported learning activities. Through an in-depth analysis of the discussions and interactions of the FoLA^2 stakeholders, we gain valuable insights into how these stakeholders navigate the topic of LA and its implications within the learning context.

Overall, our evaluation study of FoLA^2 not only fills a gap in evaluating the practical usage of LA design methods but also provides a comprehensive understanding of how such methods can improve technology acceptance and facilitate collaborative efforts among stakeholders. This contributes to the advancement of knowledge in the field of LA and offers a valuable framework for evaluating similar methods in the future.

2 Background

In this background chapter, we provide some more details about the field of LA-supported LD as well as the FoLA^2 design method, which is a specific example for the facilitation of LA-supported LD.

2.1 Learning Analytics supported Learning Design

Since the early 2000s, LD has been gaining prominence, merging educational science, subject domain, and technology-enhanced learning to create a universal markup language for educational activities [12],[13]. LA presents opportunities to enhance the quality of education by capturing, analyzing, and visualizing learning and teaching behaviors [14]. However, the majority of educational institutions currently restrict the use of LA to tracking digital user activity in existing databases. They overlook the limitations of already saved log-data that is not made for LA purposes like providing highly informative feedback to students [15]. Recent trends indicate a growing interest in integrating LA with LD practices [16] to gain more relevant data to understand the context of the learning process and provide informative feedback. Furthermore, considering LA already at the design stage of a learning activity or course facilitates more adaptive and personalized learning experiences for the students as well as encourages engagement with LA on the teacher's side. Despite the steady growth of LA research over the past decade, its adoption by educational institutions and teaching staff remains limited [17]. To address this challenge and promote the widespread implementation of LA in educational settings, we have developed the $FoLA^2$ method to facilitate the practical use of LA-supported LD.

2.2 The Fellowship of Learning Activities and Analytics ($FoLA^2$)

$FoLA^2$ [18] is a method that is structured according to the Design Cycle for Education [19] to design learning activities while already taking possible technology and learning analytics into account during the design process. The $FoLA^2$ design method provides an interactive and educational approach to exploring the design and implementation of learning activities. It serves as a framework that engages participants in a simulated environment, facilitating a deeper understanding of the principles and practices of learning analytics and learning technologies. Through the $FoLA^2$ method, participants actively collaborate, critically analyze, and make informed decisions, delving into the intricacies of designing effective learning activities while leveraging data-driven insights. This method enables educators, researchers, and practitioners to explore diverse roles and perspectives, tackle challenges in learning activity design, and harness the potential of analytics for enhancing educational practices. The $FoLA^2$ method fosters engagement, knowledge exchange, and skill development among professionals in the field of learning analytics and learning technologies. The method comprises eight sequential steps for participants to follow. Initially, role cards are distributed to assign specific roles and provide guiding questions (Step 0). Next, participants select a learning activity, declare its intention, and choose student and teacher cards representing the target group (Step 1). An organizational challenge or input requirements are introduced (Step 2), followed by sharing best, good, and bad practices to gain inspiration and learn from past decisions (Step 3). Participants then analyze different learning activity types and select a pedagogy or educational vision (Step 4). In the development phase, they design a sequence of interactions, considering the availability of Learning and Educational Technologies (LETs) for each interaction (Step 5). Indicators or items are selected for each interaction, and measurement tools and data elements are determined (Step 6). The choices made in interactions, LETs, and indicators are evaluated in a simulation, assessing alignment with the population's characteristics and making adjustments if necessary (Step 7). Finally, participants have the option to adapt their choices based on the simulation outcomes (Step 8). This comprehensive approach ensures a structured and systematic process for utilizing the method effectively. $FoLA^2$ can also be seen as a serious game, due to its eight-step structured approach, the use of a play board that is placed in the middle of the participants, and the set of cards that are used in the eight steps.

3 Methods

The methods section provides an overview of the chosen mix-methods approach. It provides overviews of technology acceptance models, discourse analysis methods, and a detailed description of epistemic network analysis to research the adoption of LA. It presents the research questions that guide the study, details about the participants and materials, and the procedural steps followed. Additionally, it includes two subsections focusing on the analysis using ENA, describing the data processing and analytical techniques employed. Overall, this section provides a comprehensive understanding of the research framework and methodology for investigating the adoption of LA.

3.1 Overview of technology acceptance models for the adoption of LA

Different acceptance models have been used to evaluate what influences LA tooling acceptance. Rienties et al. [20] investigated the acceptance of dashboards. Ali et al. [21] developed a Learning Analytics Acceptance Model to get insight into the acceptance of LA tooling, and Scheffel et al. [22] included constructs like awareness in their evaluation framework for learning analytics. Mavroudi et al. [23] recently published a TAM-based acceptance of the LA model for people who watched informative videos on LA. In our case, however, it is not a specific LA tool that needs to be evaluated on an acceptable level by stakeholders, but we investigate if and how FoLA^2 engages participants in using and accepting LA. Therefore, we chose a general acceptance model, the UTAUT2, that was developed by Venkatesh et al. [24]. We followed examples [25], [24] mentioned in a literature review on UTAUT2 [26] to create a UTAUT2-based questionnaire that we used before and after using FoLA^2.

3.2 Using UTAUT2 to research the adoption of LA

The key-subscales in our UTAUT2-based questionnaire were Performance Expectancy (PE), Effort Expectancy (EE) and Behavioral Intention (BI). PE is defined as the degree to which an individual believes that using the system will help a person attain gains in job performance. Previous research reported that performance expectancy was a significant predictor of behavioral intention [25]. Questions used are: PE1: I think LA is useful during my work, PE2: By using LA I finish my task faster or better, PE3: By using LA, I raise my productivity, PE4: If I use LA, then I will improve my chances of a positive review, and PE5: In general, I think it is an advantage to use LA. EE is the degree of ease associated with the use of the system. Previous research supports the idea that latent variables related to effort expectancy are significant in determining a person's intention to adopt new technology [27], [24]. Questions used are: EE1: It would be easy for me to become skilled at using LA, EE2: I would find LA easy to use, EE3: Learning to operate LA is easy for me, and EE4: I find it easy to get LA to do what I want. BI 'is the perception of to what degree a person has formulated conscious plans to (not) perform a certain specific future behavior' [28]. In our research context, behavioral intention shows how much a participant intends to use LA when teaching or learning. To really study the relationship between behavioral intention and use, a longitudinal design is preferred because intention is based on a future behavior and use is based on a current behavior. However, even with a survey study, it is possible to study the relationship between behavioral intention and use. Only Agudo-Peregrina et al. [29] found that behavioral intention and self-reported frequency of use of e-learning systems like virtual learning environments and learning management systems had a positive, although not strong, relationship. Questions used are: BI1: I intend to continue using LA in the future, BI2: I will always try to use LA in my work life, BI3: I plan to continue to use LA frequently, BI4: I will often use LA in the future, and BI5: I will recommend others to use LA.

3.3 Overview of discourse analysis methods for the adoption of LA

Several methods are available to analyze discourse in co-creation sessions comprehensively. These methods include qualitative content analysis, thematic analysis, discourse analysis, grounded theory, conversation analysis, and Epistemic Network Analysis (ENA). Qualitative content analysis [30],[31] and thematic analysis [32],[33] focus on capturing and interpreting the content of discourse. Discourse analysis [34],[35], grounded theory [36],[37], and conversation analysis [38],[39] consider both the content and context of discourse. ENA, on the other hand, offers a distinct advantage by representing discourse as a network of interconnected ideas and concepts [40]. While each method has its strengths, ENA provides a unique approach to analyzing discourse by visualizing the relationships and connections between ideas, enhancing the understanding of complex networks within the discourse.

3.4 Using Epistemic network analysis to research the adoption of LA

ENA is a quantitative ethnographic technique that models the structure of connections in data. It assumes the systematic identification of meaningful features (codes) in the data, the presence of local structure (conversations), and the importance of code connections within conversations [40], [41], [42]. By quantifying code co-occurrences, ENA creates weighted networks and associated visualizations for each unit of analysis. Importantly, ENA analyzes all networks simultaneously, allowing for visual and statistical comparisons. Unlike traditional categorization and interpretation, ENA visualizes relationships between ideas and the overall knowledge structure, revealing central ideas, sub-topics, and information flow. It combines qualitative and quantitative dimensions, enhancing decision-making, knowledge sharing, and collaboration in co-creation sessions. By uncovering hidden relationships and facilitating visual understanding, ENA promotes effective communication and collaboration among participants, leading to more informed outcomes. Thus, ENA is a valuable tool for analyzing discourse in co-creation sessions, offering a comprehensive perspective that fosters deeper understanding and improved collaboration. Furthermore, ENA has been applied in the past to research the adoption of LA as well as LA-supported design methods. The research of Zhang et al. [43] is highly relevant for our research because it shows the analysis of the discourse of primary school teachers learning how to use TPACK, a theory that explains the set of knowledge a teacher needs to teach students effectively with the help of technology [44], [45]. In this case, it is an online active learning discussion, but TPACK ordering and coding illustrate a possible way to get insight into what is learned. Bressler et al. [46] present an ENA analysis of the effects of a serious game on scientific research practice. They used essential elements from the theory of scientific research used in practice as codes and compared the usage of the serious game, an active learning tool. For a robust ENA analysis, a grounded coding scheme for the topic should be selected. The playing cards, collaboration, and discussions on LA topics were investigated with ENA [47]. ENA was employed to analyze the discourse in a sample of fourteen co-design sessions utilizing the FoLA^2 method. A code book for LA practice was established based on the framework presented by Greller and Drachsler [14]. Transcriptions of sound recordings of the collaborative FoLA^2 design sessions were coded and subjected to ENA analysis, focusing on the six critical dimensions of the LA framework.

3.5 Research questions

We have formulated the following research questions to investigate if and how FoLA^2 helps with the adoption of learning analytics-supported learning design according to the technology acceptance model UTAUT2 (see Section 3.2).

RQ1a): How does the use of FoLA^2 change the performance expectancy of LA?

RQ1b): How does the use of FoLA^2 change the effort expectancy of LA?

RQ1c): How does the use of FoLA^2 change the intention to use LA?

We have formulated the following research questions to analyze the discourse among the collaborative sessions while using FoLA^2 with the network analysis tool ENA (see section 3.4):

RQ2a) How do the stakeholders collaborate, while sharing LA concepts when using FoLA^2?

RQ2b) What relevant LA concepts are shared by stakeholders when using FoLA^2?

3.6 Participants and Material

Teachers, students, and educational-oriented advisers from the ICT Academy of Zuyd University of Applied Sciences gathered during fourteen design sessions in October 2020. Four or five participants co-designed learning activities with the FoLA^2 for the first-year bachelor courses `team skills' and `quantitative methods.' The learning activities were implemented in these two courses, which ran five to ten weeks after the design sessions. The first six weeks of these courses contain the following learning activities: lecture, discussion group, workgroup, and self-study. Each of the remaining three weeks contains a discussion group, a workshop, self-study, and group work (a case study). We chose to design discussion groups for our study as they are complex learning activities where the division of interaction between students and teachers is around 50/50, compared to the design of discussion groups, lectures, or workshops, where the design complexity is lower. The design sessions took place amid the COVID-19 pandemic, when varying levels of contact restrictions applied. A varying number of people were allowed to be present, i.e., there were six participants in the first four sessions for the `team skills' course and five participants in both the remaining three `team skills' sessions and all seven `quantified methods' sessions.

Table 1. Participants. Nr. is number. Min. is minimum. Max. is maximum, Avg. is average, and Exp. is expertise. TELLAs are Technology Enhanced Learning Advisors and Learning Analytics Advisors. EAIDs are Educational Advisors, Assessment Advisors and Instructional Media Designers. All Advisors combine all advising roles.

Roles	Nr.	Min. Age	Max. Age	Avg. Age	Min. Exp.	Max. Exp.	Avg. Exp.	Male	Female
TELLAs	4	47	59	56	8	13	11.7	1	3
EAIDs	4	39	64	49.8	0	10	8	4	0
All Advisors	10	36	64	51.3	1	20	11.6	5	5
Students	14	19	27	23.2	0.16	9	4.4	13	1
Study Coaches	14	28	56	41.5	0	14	4.9	12	2
Teachers	14	28	64	44.1	1	40	9.5	13	1

Participants had the following roles:

- a Game Master (the same person in all sessions) led through all sessions and monitored time, outcomes, and the general process;
- a Student (a different person in each session);

- a Teacher (a different person in each session);
- a Study Coach (twelve persons participated once, two participated twice);
- a Technology-Enhanced Learning/Learning Analytics (TELLA) advisor (one person participated three times, one participated once);
- and an Educational/Assessment/Instructional Design (EAID) advisor (nine persons participated once, one participated two times).

After the first four sessions, the last two roles became one role ('All advisors'). Participants in advisory roles may have participated in different sessions with different roles. Participants were selected based on their availability and willingness to participate. Participating educational-oriented advisers had some expertise in their advising role, and the chosen teachers had a connection to the content topic of the chosen design. Students were purely selected based on availability. Table 1 shows the demographic data of the participants.

3.7 Procedure

Participants took part in a two-hour session in a room prepared according to COVID-19 regulations. At the beginning of the session, participants signed an informed consent to permit the collection of all their audio during the experiment; they also filled out a questionnaire on demographic data, questions about their experience in education, and the UTAUT2 [24] questions.

Participants watched a video introduction to the method[1]. After watching the video, the participants were able to ask questions to the Game Master to clarify the assignment. A set of playing cards was laid on each player's position, and a whiteboard pen (for writing on blank cards) was available. Specific role cards introduced the roles, and each position had an individual recording device. Two enlarged cards of the pedagogy `Discussion Group' and two documents with all course activities were on the table. The Game Master had a laptop for registration purposes (see Figure 1) and started by explaining which course and what learning activity were to be designed. The game consists of several phases coded by the colors: white, gray, blue, red, and yellow. During each of these phases, the Game Master took a photo of every board state. At the end of each session, participants answered the same UTAUT2 questions again.

1 https://www.youtube.com/watch?v=fLz5dE4g81k

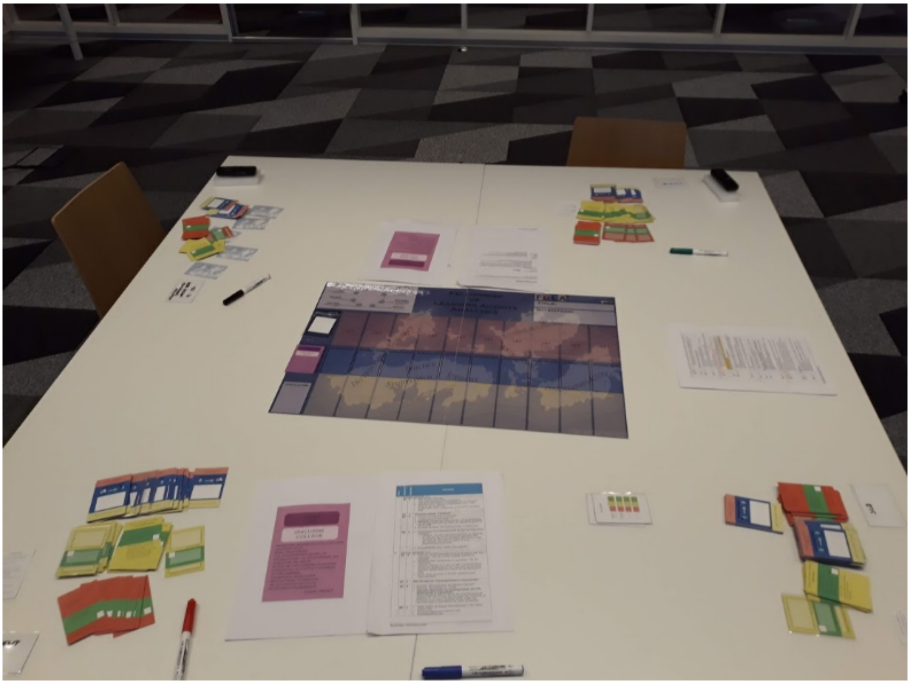

Fig. 1. Experimental setup

3.7.1 UTAUT2 technology acceptance analysis

The results of both pre- and post-questionnaires are checked for reliability and validity. First, we assessed internal consistency. The loadings of the items should be higher than 0.5 [48]. Rho Alpha should either be between 0.6 and 0.7 or preferably higher than 0.7 [49]. In the next step, we looked at convergent reliability by checking if the Average Variance Extracted (AVE) is higher than 0.5 [50, 51]. The Composite Reliability (CR) per variable should be bigger than 0.7 and smaller than 0.95 [52] indicating internal consistency. As a final step regarding the measurement model, we assessed the Discriminant Validity by looking at the cross-loadings and the Fornell Larcker criterion. Assessing Discriminant Validity means that the outer loadings of each indicator should be the highest in their column, and the Heterotrait-Monotrait Ratio should not be above 0.9 [49].

For Performance Expectancy, Effort Expectancy, and Behavioral Intent, we performed a paired t-test to examine the significance of the change between pre and post. In order to do this, we hypothesized for H_0 that the difference between Performance Expectation post and pre would be zero with alpha = 0.05.

3.7.2 ENA discourse analysis

In this study, we applied ENA to our data using the ENA 1.7.0 [53] Web Tool. We defined the units of analysis as all lines of data associated with a single value of Participant subset by Session. For example, one unit consisted of all the lines associated with Session 1. The ENA algorithm uses a moving window to construct a network model for each line in the data, showing how codes in the current line are connected to codes that occur within the recent temporal context [54], defined as 3 lines (each line plus the 2 previous lines) within a given conversation. The resulting networks are aggregated for all lines for each unit of analysis in the model. In this model, we aggregated networks using a binary summation in which the networks for a given line reflect the presence or absence of the co-occurrence of each pair of codes.

Our ENA model included the following codes: Stakeholders, Objective, Data, Instruments, External Limitations, Internal Limitations, Data-Client, Data-Subject, Objective, Open/Protected Data, Indicators, Pedagogy, Analytical, Visualisation, Conventions Norms, Ethics, Privacy, Timing, Interpretation Skills, Critical Thinking, Card Idea, Card Content, Card Discussion and Card Position. For every yellow card that is talked about in the discourse (e.g. engagement), a code is also generated. In an attempt to make the connection between the participating roles visible during the discourse, we added the separate roles (Game Master, Teacher, Student, All Advisors, and Study Coach) as codes. All the related cards (student population, teacher population, red cards, and yellow cards) are added as codes at the moment they are discussed. Coding was done by two researchers, both male, 43 and 50 years old, with 15+ years of experience in education, and was done manually in several steps. In the first iteration, one session was coded. Inter-rater reliability was lower than 0.4. In a reflective session, raters discussed the differences and came to an inter-rater reliability higher than 0.95. A second full session was coded. Inter-rater reliability was around 0.6. Again, a reflective session was done to get inter-rater reliability higher than 0.95. Then the other 12 sessions were coded, and again a reflective session and discussion took place to get the overall inter-rater reliability to 0.92.

We defined conversations as all lines of data associated with a single value of the Phases subset of Played Cards. For example, one conversation can consist of all the lines associated with a specific yellow card that is played within the Introduction Phase of the game.

The ENA model normalized the networks for all units of analysis before they were subjected to a dimensional reduction, which accounts for the fact that different units of analysis may have different numbers of coded lines in the data. For the dimensional reduction, we used a singular value decomposition, which produces orthogonal dimensions that maximize the variance explained by each dimension. (See [41] for a more detailed explanation of the mathematics; see [55] and [56] for examples of this kind of analysis).

Networks were visualized using network graphs, where nodes correspond to the codes, and edges reflect the relative frequency of co-occurrence, or connection, between two codes. The result is two coordinated representations for each unit of analysis: (1) a plotted point, which represents the location of that unit's network in the low-dimensional projected space, and (2) a weighted network graph. The positions of the network graph nodes are fixed, and those positions are determined by an optimization routine that minimizes the difference between the plotted points and their corresponding network centroids. Because of this co-registration of network graphs and projected space, the positions of the network graph nodes —and the connections they define— can be used to interpret the dimensions of the projected space and explain the positions of plotted points in the space.

4 Results

4.1. Results of the UTAUT2 technology acceptance

This section describes the differences in results between the pre- and post-UTAUT2-based questionnaires. We do so by successively addressing the pre-questionnaire reliability and validity, the post-questionnaire reliability and validity, and then the scores and exciting differences.

4.1.1. Reliability and validity of Pre Questionnaire measurement model First, we assessed internal consistency. The loadings of the items should be higher than 0.5, therefore we excluded PE1 (0.483) All items have a Rho Alpha between 0.6 and 0.7. In the next step, we looked at convergent reliability by checking that the Average Variance Extracted (AVE) is higher than 0.5 and the Composite Reliability (CR) per variable is bigger than 0.7 and smaller than 0.95 for all variables, indicating internal consistency. As a final step regarding the measurement model, we assessed the Discriminant Validity by looking at the cross-loadings and the Fornell Larcker criterion. Assessing Discriminant Validity means that the outer loadings of each indicator should be the highest in their column. A slight problem appeared as BI2 and BI5 are slightly higher than EE4 for the cross-loading of subscale Effort Expectancy, indicating that BI2 and BI5 have a little more influence on Effort Expectancy than item EE4. As differences are smaller than 0.04, we note this but leave every item in the model. The Fornell-Larcker criterion is matched; every diagonal entry (the AVE square) is the highest in their column. The Heterotrait-Monotrait Ratio is not above 0.9.

4.1.2 Reliability and validity of Post Questionnaire measurement model The internal consistency of the post model is checked. We excluded: PE4 (0.488), because it is < 0.5 [49]. Then we checked that for every item, Rho Alpha > at least 0.6, preferably 0.7 and Rho Alpha < 0.95. Next, convergent reliability was checked, resulting in all AVEs >0.5. The CR per variable is between 0.7 and 0.95 Eventually, the Discriminant Validity is assessed. The cross-loadings are within the acceptable margins. The Fornell Larcker criterion has no issues, just as the Heterotrait-Monotrait Ratio brings no problems as nothing is above 0.9.

4.1.3 Pre- and Post-scores

Looking at the average pre- and post-scores of the UTAUT2 questionnaires, we notice small differences overall. The pre-questionnaire scores are positive (> 3.5) as they range between 3.9 and 5.4. All are higher in the post-questionnaire compared to the pre-test (see Table 3). An overview of acceptance per role (see: Table 2) shows that for every role, Behavioral Intent rises (min. 0.1, max 0.28)

Table 2. Per role acceptance results

	Performance Expectancy		Effort Expectancy		Behavioral Intent	
	pre	post	pre	post	pre	post
AllAdvisors	4.91	4.88	5.56	5.50	5.40	5.50
Student	4.92	5.08	5.11	5.61	4.62	4.88
StudyCoach	4.78	4.93	5.48	5.55	5.19	5.33
Teacher	4.96	5.06	5.55	5.27	5.09	5.37
Average	4.894	4.990	5.42	5.48	5.07	5.27

As the group is collaboratively designing the learning activity, the average scores per session are interesting. Table 3 shows the pre- and post-scores per item per session.

Table 3. Pre and post session acceptance results

Session	Performance Expectancy		Effort Expectancy		Behavioral Intent	
	pre	post	pre	post	pre	post
1	4,67	5,1	5,65	5,55	5,55	5,36
2	5,48	5,16	5,65	5,75	5,6	5,72
3	4,96	5,28	5,7	5,85	5,52	5,72
4	5,44	5,16	5,05	5,25	5,7	5,45
5	4,8	4,75	5,19	5,56	4,85	5,5

6	4,8	4,8	5,88	5,75	5,45	5,3
7	4,15	4,25	5,19	5,25	4,3	4,4
8	4,3	4,35	5,38	5,56	4,9	5,05
9	5,05	4,85	5,44	5,75	5,05	5,05
10	4,73	5	5,56	5,63	4,5	5,05
11	4,95	5,53	5,13	5,38	5	5,5
12	5,2	4,9	5,31	5,81	4,55	5,13
13	4,85	4,9	5,44	4,63	4,65	4,7
14	4,75	5,6	5,44	4,94	5,7	5,85
Average	4,866	4,974	5,427	5,475	5,094	5,270

For Performance Expectancy, Effort Expectancy, and Behavioral Intent, we performed a paired t-test to examine the significance of the change between pre and post. In order to do this, we hypothesized for H_0 that the difference between Performance Expectancy post and pre would be zero. With alpha = 0.05 we found P = 0.15 and could not reject H_0. We also hypothesized for H_0 that the difference between Effort Expectancy post and pre would be zero. With alpha = 0.05 we found P = 0.30 and could not reject H_0. Both positive changes after playing FoLA^2 were not significant. On the other hand, we also hypothesized for H_0 that the difference between Behavioral Intent post and pre would be zero. With alpha = 0.05 we found P = 0.01. So, in this case, we reject H_0 and assume that the positive difference of 0.17 is significant.

4.2. Results of the ENA of the discourse

This section describes the results of the ENA of the discourse of the fourteen times of FoLA^2 use. First, we look at the results concerning the collaboration betwen the different participants. Secondly, we will look at the LA content discussed. There are 12,695 discourse items in fourteen sessions, with an average of 906 (min: 471, max: 1559). Each discourse item is a transcribed sentence spoken out by one of the participants. Our model had co-registration correlations of 0.97 (Pearson) and 0.98 (Spearman) for the first dimension and co-registration correlations of 0.97 (Pearson) and 0.97 (Spearman) for the second. These measures indicate a strong goodness of fit between the visualization and the original model.

4.2.1 Collaboration

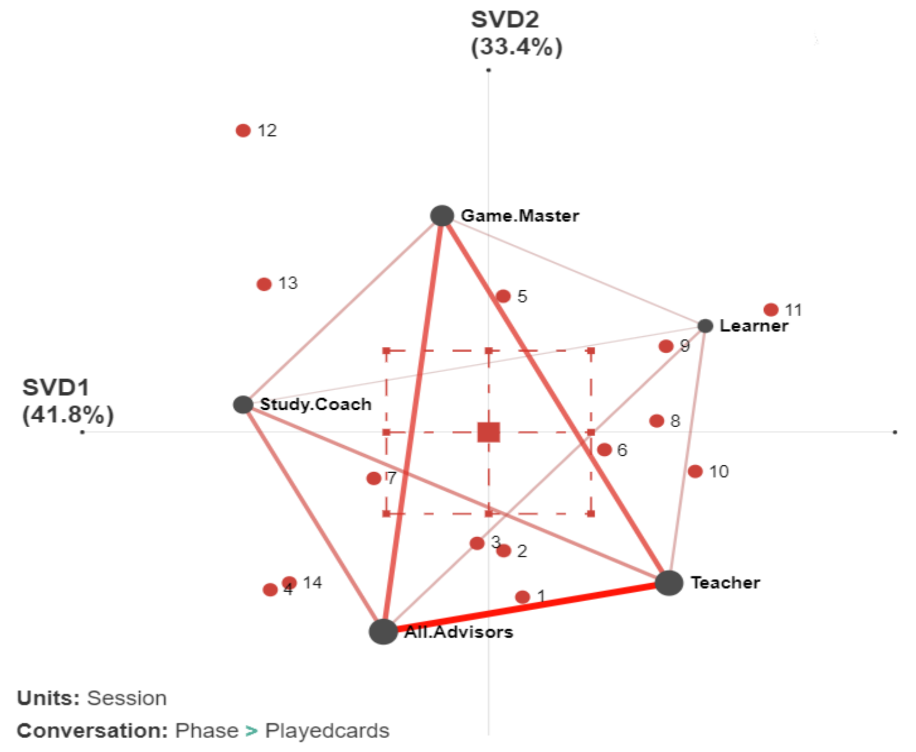

Figure 2. Turn taking per role and interactions all sessions

In our first analysis to investigate collaboration (Figure 2), the units we chose were the sessions. The conversation is based on the phase of the method combined with the played-card. In other words, we investigate each conversation on a playing card in a specific phase of the method. We looked at the codes: Teacher, Student, All Advisors, Study Coach, and a Game Master. A score is counted if a specific participant talks about a card. Each of the fourteen sessions is marked with a red dot and labeled in Figure 2. Each red dot produces a graph of black dots. The black dots represent how much a role actively participated in a conversation about a topic; the bigger the dot, the more significant their contribution. The lines between the dots represent the times two roles engaged in a discussion about a topic. Figure 2 is a visualization of the mean (red square) of all fourteen sessions. In this example, All Advisors and Teacher have discussed more within conversations than the Study Coach and Learner. SVD1, 41,8% and SVD2 33,4% represent the amount of variance in the graph accounted by the dimensions.

In another analysis to get insight into the collaboration (Figure 3), the units we chose were the participants (roles). The conversation is based on the phase of the method combined with the played card. We looked at the usage of the codes:

Stakeholder, Data, Instruments, Internal Limitations, External Limitations, and Objectives to make a visualization. We have done this for the five participating roles (red dots labeled Teacher, Learning, Study Coach, All Advisors, and Game Master). Each red dot produces a graph of black dots. The size of the black dots represents the number of mentions of a topic in a conversation by that role. Lines between two dots represent when both topics occur in one discussion. Figure 3 illustrates the mean (red square) of all five roles. In this example, Objectives and Data are mentioned a lot (bigger black dots) and are often mentioned in combination (thicker red line) in comparison to Stakeholders and External Limitations, which are used less in combination (thinner line).

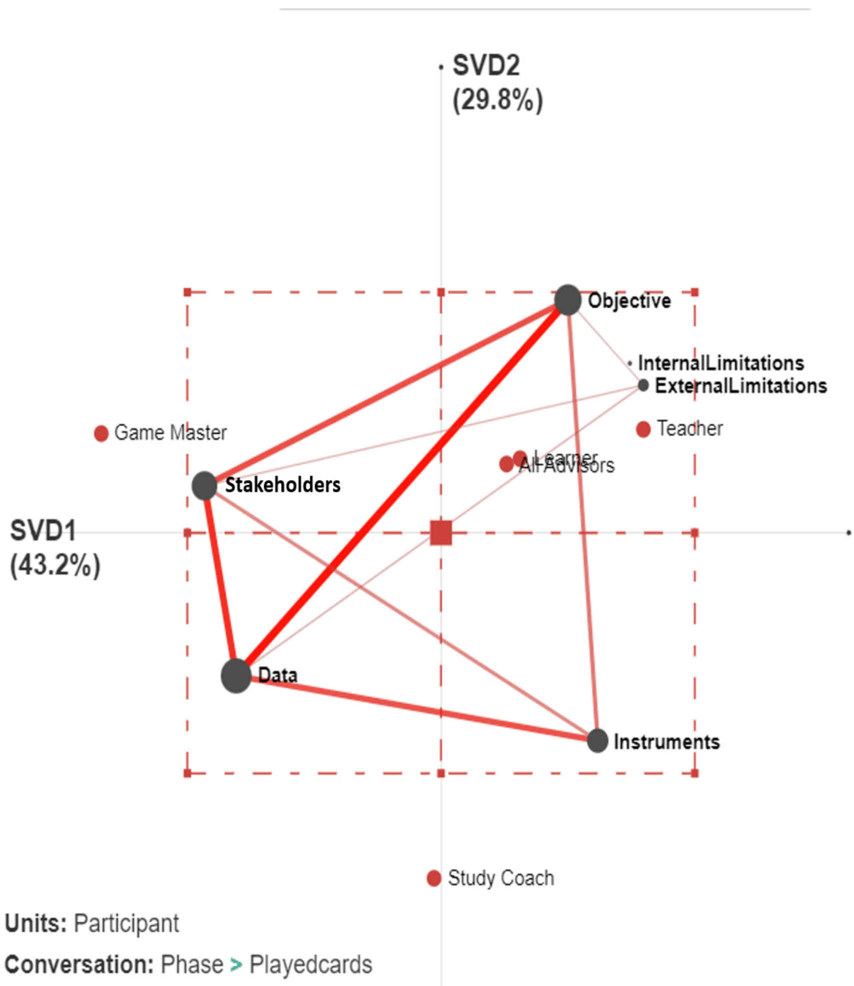

Figure 3. Topic coverage mean all participants

4.2.2. LA content discussed

For an analysis of the LA content discussed (Figure 4) the units are all fourteen sessions. The conversation is based on the phases of a session combined with the played-card. In other words, we investigate each conversation on a playing card in a specific phase of the sessions. We looked at the usage of the codes in fourteen sessions: Stakeholders, Data, Instruments, Objective, External Limitations, and Internal Limitations to make a visualization. Each red dot produces a graph of black dots. The black dots represent topic usage in a discussion, multiple usage results in bigger dots. Lines between two dots represent the use of two topics in one discussion. Figure 4 illustrates the mean (red square) of all 14 sessions. In this example, Data and Objectives have been the topic of discussion more often than Internal Limitations, which were not used in connection with other words. SVD1, 43,2%, and SVD2 29,8% represent the amount of variance in the graph accounted for by the dimensions.

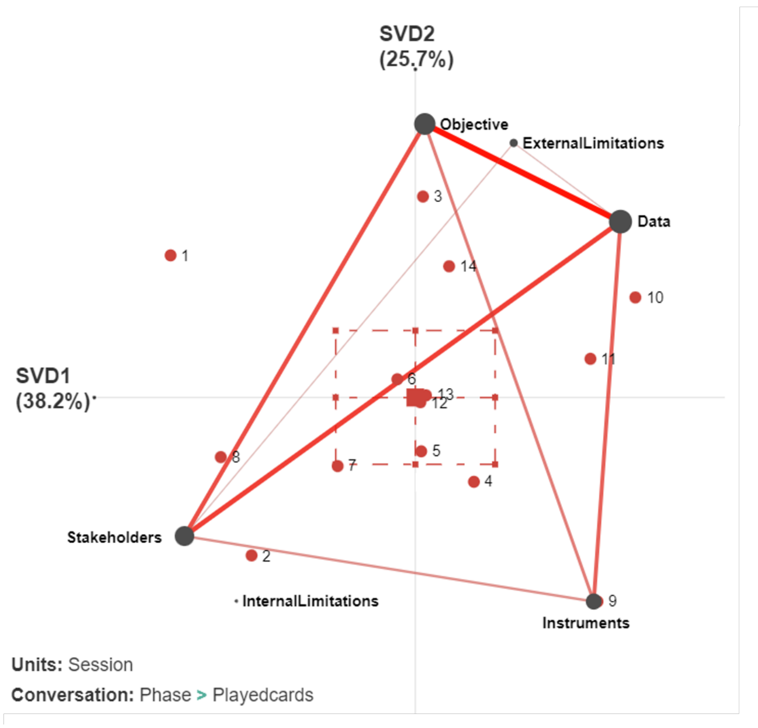

Figure 4. Topics of the mean of all sessions

In the second analysis of the topics covered, we investigated if there was a difference between the two courses. Seven of the fourteen courses were part of Course A (Team skills), and the other seven were part of Course B (Quantified methods). The question was whether the courses triggered a significant difference in the usage of topics.

Figure 5 illustrates the analysis. Units were sessions, and the conversation is the phase combined with the played card. We looked at the usage of the codes: Stakeholders, Data, Instruments, Objective, External Limitations, and Internal Limitations to make a visualization. We see a combined view (Course A – Course B) and, for both courses, an individual view. Course A sessions are colored blue and labeled *Course A.sessionnumber*, Course B sessions are colored red and labeled *Course B.sessionnumber*. In Figure 5, we see the mean of the seven sessions of Course A (blue, top) and the mean of the seven sessions of Course B (red, bottom). The black dots represent how much a topic is used in a conversation; the bigger the dots, the more often the topic is used. The thickness of the lines between two topics illustrates how often they are used together in one discussion. In the combined graph, we see the differences between both courses. Data and stakeholders have been discussed more in combination in Course A sessions, while Data and Instruments have been discussed more in Course B sessions. SVD1, 38,2% and SVD2 25,7% represent the amount of variance in the graph accounted by the dimensions. Along the X axis, a two sample t test assuming unequal variance showed Course A (mean=-0.65, SD=1.13, N=7) was not statistically significantly different at the alpha=0.05 level from Course B (mean=0.65, SD=1.51, N=7; t(11.12)= 1.81, p=0.10, Cohen's d=0.97). Along the Y axis, a two sample t test assuming unequal variance showed Course A (mean=-0.01, SD=1.33, N=7) was not statistically significantly different at the alpha=0.05 level from Course B (mean=0.01, SD=1.14, N=7; t(11.73)= 0.02, p=0.99, Cohen's d=0.01).

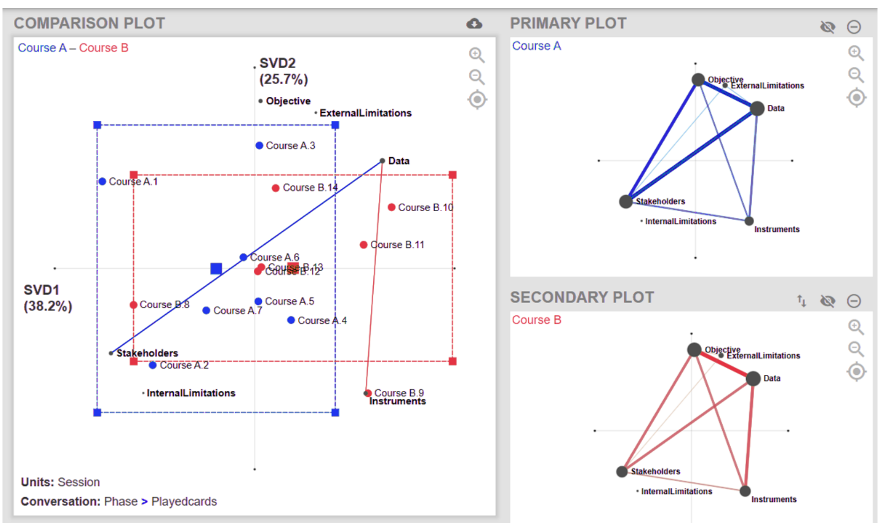

Figure 5. Course A versus Course B, usage of topics

A third analysis on the coverage of LA topics was done by investigating if there was a big difference between the roles, i.e. whether any of the roles triggered a significant difference in the usage of topics. Figure 6 illustrates one of the analyses between roles: Teacher versus learner. Units were participants; the conversation is the phase combined with the played card. We looked at the usage of the codes: Stakeholders, Data, Instruments, Objective, External Limitations, and Internal Limitations to make a visualization. We see a combined view (Teacher - Learner) where the blue square is the mean of all participants, blue dots labeled *Teacher.sessionnumber*, and pink dots labeled *Learner.sessionnumber*. On the right side of Figure 6 we see the graph of the Teacher (blue, top) and the graph of the learner (pink, bottom). The black dots represent how much that role in a conversation uses a topic. The thickness of the lines between the topics illustrates how much both topics are used in one discussion. The combined graph shows how all teachers discussed the fourteen sessions compared to how all learners discussed the fourteen sessions. The teachers used Data and Objectives more in their discussions and used Instruments and Objectives more. The learner connected Data with Stakeholders in their discussions and used the combination of Stakeholders and Instruments more often. SVD1, 51.5% and SVD2 41.8% represent the amount of variance in the graph accounted by the dimensions. Along the X axis, a two sample t test assuming unequal variance showed Teacher (mean=-0.17, SD=0.98, N=14) was not statistically significantly different at the alpha=0.05 level from Learner (mean=0.27, SD=1.07, N=14; t(25.82)= 1.14, p=0.27, Cohen's d=0.43). Along the Y axis, a two sample t test assuming unequal variance showed Teacher (mean=0.38, SD=0.56, N=14) was not statistically significantly different at the alpha=0.05 level from Learner (mean=-0.05, SD=0.91, N=14; t(21.74)= -1.48, p=0.15, Cohen's d=0.56).

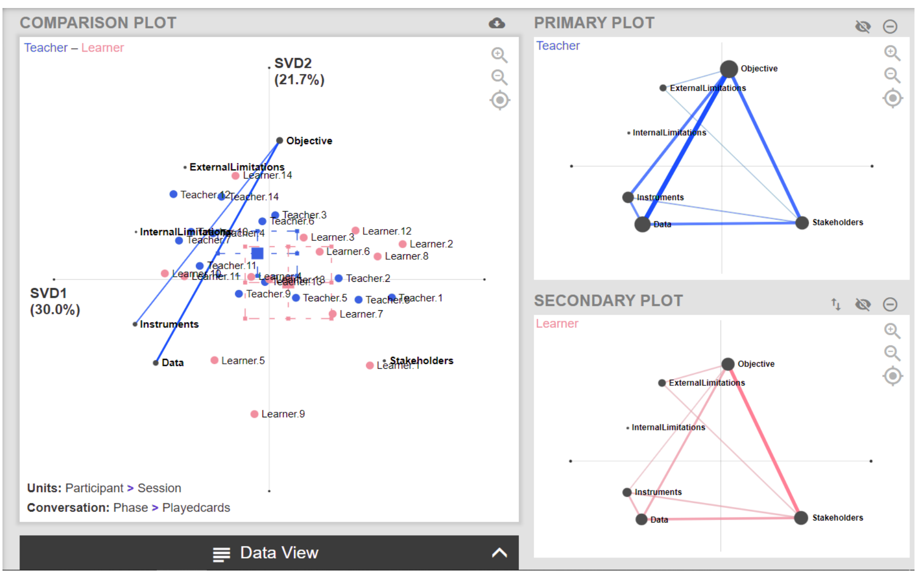

Figure 6. Teacher versus Learner, usage of topics

We did these analyses for all roles. Results differed topic-wise, but the differences were not statistically significant.

5 Discussion

$FoLA^2$ is a method that helps teams with heterogeneous stakeholders to design learning analytics supported activities. In our study, every group came up with several solutions for the what-you-want-to-know cards (i.e. the LA-related cards) and how to implement them in practice. It should be highlighted that using and choosing LA in the design phase of the activities does not guarantee usage during run-time. Nevertheless, the numbers are positive and encourage us to pursue the further implementation of this process. Furthermore, one could see the amount of usage during the design phase as an indicator of the contribution $FoLA^2$ brings toward LA-supported LD, however, the embedding of LA into learning activities could also mean "less is more," i.e., more LA elements do not necessarily mean higher actual usage of LA for the participants. In other words, a higher number of LA elements does not automatically mean an effective and supportive LA.

The average pre-score for performance expectancy (4.8) with the lowest session score (4.15) shows the participants' very positive base attitude. Still, after using $FoLA^2$, it slightly rises among the Student, StudyCoach, and Teacher in the average sessions. Looking at the individual sessions, we counted eight sessions with higher expectancy performances and one with an equal LA performance after the sessions. So we can say as an answer to **RQ1a** that the use of $FoLA^2$ changes the performance expectancy positively in the majority of cases.

The average effort expectancy was high (5.4) in the pre-session, which means that participants were confident that they could quickly learn to use LA in their practice. The average post score increased slightly, but we see that the Teacher's effort expectancy lowers after using $FoLA^2$ when looking at the roles. The Student and Study Coach show a positive change in effort expectancy. Looking at individual sessions, we can see that the effort expectancy rises in ten sessions. In answer to **RQ1b** we can also say that in the majority of sessions and roles, the effort expectancy rises, the Teacher is however, an important exception. The intention to use LA is also relatively high (5.1) for the session. It grows after using the method, and all individual roles show this growth. The post-score on intention to use was equal in one session and has risen in ten sessions. Looking at the average values of the pre-questionnaire for individuals, roles, and groups, we notice relatively high scores per variable prior to the session. Even with the high pre-score, we see a statistically significant rise in the post-questionnaire. Our answer to **RQ1c** is that the intention to use LA after using $FoLA^2$ has risen. Intention to use is one thing, using another. The designs of both courses made with $FoLA^2$ were implemented in October 2020. The workload and adaptations needed to be made in practice during COVID-19 restrictions were too large to make a conclusive observation of the designed learning activities.

The ENA visualizations based on the roles, both on the LA topics and the collaboration between the roles, show that the different roles have their influence on the use of the Learning Analytics topics in the group and have a contribution to the collaborative knowledge creation with each other. It shows that the different roles have different input and purposes in the discussion and illustrates how the individual roles collaborate while exchanging LA knowledge. Further research is needed to exactly show what each role contributes and how collaboration between the roles triggers collaborative knowledge creation, but the method shows us answers on how stakeholders collaborate using FoLA^2 and thereby answers **RQ2a**. The active and distinctive input of the Learner role supports the idea of involving learners in the co-design of LA, as is also pointed out by other researchers [54]. In the experiment, there was some relevant experience in playing the role for all participants (i.e. the teachers were teachers, the study coaches were study coaches). In practice, inexperienced participants can play the role (i.e., a teacher with no experience in Study Coaching could play the Study Coach). It is interesting to see if, in these situations, all roles combined have complete coverage of LA topics. Further research should shed more light on this.

Analyzing the discourse of the sessions, we can see that in the overview of all fourteen sessions, all relevant LA topics seem to have been covered. Not every session covers each topic the same way, but differences are statistically not significant, as seen in the distinction between the two sets of designed activities per course. The distribution of LA topics illustrates how LA-relevant topics are exchanged and connected by the stakeholders in the fourteen sessions. The ENA visualizations gave insights to answer **RQ2b** and showed what relevant LA concepts are shared while using FoLA^2. We especially noticed that Internal Limitations, in the detailed view represented by Critical Thinking and Interpretation, were underrepresented in our recorded sessions. One of the reasons for this could be the participants' overconfidence, as they are all IT professionals or students, and they do not see these topics as a discussion point. Another reason could be not having experienced LA in practice. All participants have limited practical experience in LA within LD, which could lead to not knowing the importance of Critical Thinking or the need for Interpretation skills among students and teachers.

6 Limitations

The fourteen sessions with FoLA^2 took place in October 2020, during the COVID-19 pandemic. After four sessions, the maximum number of people allowed in a room was reduced, and in all sessions, there was a minimum distance of 1.5 meters between people. These adjustments affected the co-creation of learning activities and required adjustments in analyzing the survey data regarding the different roles. The maximum number of participants was five and was reduced to four, while there are eight roles in the game to play.

The present study was done in technology-oriented courses. The students and teachers involved can be expected to have a higher affinity for technology than other students. This limits the generalization of the outcomes of this study. Although in each session a unique teacher and student participated, several sessions had participants who had already participated in different roles in other sessions. This was due to last-minute cancellations regarding COVID infections. This could introduce some noise in the acceptance data.

To gain insight into how the method works with as many different people as possible, we chose to compile fourteen different groups per session. ENA provided insight into which LA topics were discussed by which group members. However, ENA is more suitable for comparing two distinct groups or the same group at two different times. Therefore, the interpretation of the ENA data becomes more complex.

7 Conclusion

We used $FoLA^2$ to co-create fourteen learning activities in design sessions with different groups of participants. We examined the shift in acceptance of LA before and after each design session, as well as how the group addressed LA-related topics in the discourse while utilizing $FoLA^2$. During each session, several LA elements were added to the learning activity. Further results were the insights into the changes in expectancies (PE, EE, BI) of the total sample of sixty participants towards LA after using $FoLA^2$. The final results provided by ENA gave insights into who contributed to the LA elements during the co-creation discussions.

This study presents a collection of fourteen cases that exemplify the process of educators' planning, designing, implementing, and evaluating learning designs supported by LA. By doing so, it responds to the call made by McKenney and Mor's and Mangaroska [57] for a deeper understanding of how educators engage in these processes. The reflections and interpretations of LA in conjunction with LD provided by the diverse participants, as illustrated through ENAs, demonstrate how LA is utilized to refine and redesign learning activities, aligning with the recommendations put forth by Wise et al. [58].

Our research findings demonstrate a significant increase in the usage, acceptance, and engagement of LA when employing the $FoLA^2$ method. To further validate and generalize our findings, future research endeavors should encompass diverse educational contexts and involve a larger sample size. Additionally, for the ENA study, the development of advanced automatic tools and improved discourse recording and transcription mechanisms is imperative to enhance the quality and real-time usability of the analysis. Conducting longitudinal studies with groups over extended periods will provide valuable insights into the progression of insights, awareness, and acceptance of LA, enabling more comprehensive information retrieval through the utilization of ENA and UTAUT2 methods.

The examination and analysis of the documented thinking and discussion regarding design choices present a promising prospect for surpassing the existing state of no structural and embedded utilization of LA. Upon assessing the pre- and post-acceptance models, a marginal increase in the values of indicators becomes apparent. Moreover, when examining individual, role-specific, and group-level perspectives, a higher number of indicator values exhibit an upward trend compared to those displaying a decline. These positive outcomes provide sufficient evidence to assert that the utilization of the $FoLA^2$ method contributes to increased engagement with LA among participants who already exhibit a relatively positive disposition towards it. Thus, our study not only contributes to the initial evaluation of a promising method but also establishes a framework for evaluating similar approaches in the future.

Through our study, we make a significant contribution to the field by providing the first evaluation of a promising design method. Specifically, our research focuses on evaluating the effectiveness and practical application of the FoLA^2 method. By conducting a comprehensive evaluation of FoLA^2, we offer valuable insights into its potential benefits, limitations, and overall efficacy in the context of LA. Furthermore, our study goes beyond the evaluation of a single method and could be generalized to other design methods. By establishing a rigorous evaluation framework and methodology, we provide a roadmap for future research endeavors that seek to assess and compare similar approaches in the field of LA. This contributes to the expansion of knowledge and understanding within the domain, allowing for more informed decision-making when selecting and implementing suitable design methods for LA initiatives. For future studies of this kind, we would like to apply the same mix-method approach to investigate FoLA^2 design teams over a longer time period that contains the design and development of multiple LA-supported LDs. We would then expect to see an increasing homogeneity of the terms used among the stakeholders, which can also be measured and visualized with the proposed set of research methods.

In summary, our study not only advances the understanding of a specific collaborative design method, FoLA^2, through its comprehensive evaluation but also extends its impact by showcasing the potential for evaluating and comparing similar methods. This contributes to the growth and development of the field by establishing a solid foundation for evidence-based decision-making and the continuous improvement of LAs practices.

References

[1] N. Law and L. Liang, "A multilevel framework and method for learning analytics integrated learning design.," Journal of Learning Analytics, vol. 7, no. 3, pp. 98-117, 2020. https://doi.org/10.18608/jla.2020.73.8

[2] G. Pishtari, M. J. Rodríguez-Triana, E. M. Sarmiento-Márquez, M. Pérez-Sanagustín, A. Ruiz-Calleja, P. Santos, L. P. Prieto, L. P. Prieto, S. Serrano-Iglesias and T. Väljataga, "Learning design and learning analytics in mobile and ubiquitous learning: A systematic review," British Journal of Educational Technology, vol. 51, no. 4, pp. 1078-1100, 2020. https://doi.org/10.1111/bjet.12944

[3] S. K. Banihashem, O. Noroozi, S. v. Ginkel, L. P. Macfadyen and H. J. Biermans, "A systematic review of the role of learning analytics in enhancing feedback practices in higher education.," Educational Research Review, vol. 37, p. 100489, 2022. https://doi.org/10.1016/j.edurev.2022.100489

[4] O. Nguyen, B. Rienties and D. Whitelock, "Informing learning design in online education using learning analytics of student engagement.," Open world learning: research, innovation and the challenges of high-quality education, pp. 189-207, 2022. https://doi.org/10.4324/9781003177098-17

[5] V. Kelt, R. Briers, T. Britton, M. B. Brown and K. Brook, "Enhancing Teaching and Learning through Educational Data Mining and Learning Analytics.," Computers and Education, vol. 5, p. 2456246, 2022.

[6] L. P. Macfadyen, L. Lockyer and B. Rienties, "Learning Design and Learning Analytics: Snapshot 2020," Journal of Learning Analytics, vol. 7, pp. 6-12, December 2020. https://doi.org/10.18608/jla.2020.73.2

[7] Q. Nguyen, B. Rienties and D. Whitelock, "A Mixed-Method Study of How Instructors Design for Learning in Online and Distance Education," Journal of Learning Analytics, vol.

7, p. 64-78, 2020. https://doi.org/10.18608/jla.2020.73.6

[8] M. R. Gruber, Designing for Great Teaching with Learning Design Cards.

[9] C. P. Alvarez, R. Martinez-Maldonado and S. B. Shum, "LA-DECK: A card-based learning analytics co-design tool," in Proceedings of the tenth international conference on learning analytics & knowledge, 2020.

https://doi.org/10.1145/3375462.3375476

[10] Y. Vezzoli, M. Mavrikis and A. Vasalou, "Inspiration cards workshops with primary teachers in the early co-design stages of learning analytics," in Proceedings of the Tenth international conference on learning analytics & knowledge, 2020. https://doi.org/10.1145/3375462.3375537

[11] H. Plattner, "An introduction to design thinking process guide," The Institute of Design at Stanford: Stanford, 2010.

[12] R. Koper, (2005). An introduction to learning design. In R. Koper & C. Tattersall (Eds.), Learning design (pp. 3-20). Springer. https://doi.org/10.1007/3-540-27360-31 https://doi.org/10.1007/3-540-27360-3_1

[13] R. Koper (2006). Current research in learning design. Educational Technology & Society, 9(1), 13-22. https://www.jstor.org/stable/10.2307/jeductechsoci.9.1.13

[14] Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. Journal of Educational Technology & Society, 15(3), 42-57.

[15] Drachsler, H. (2023). Towards Highly Informative Learning Analytics. Open Universiteit. ISBN: 978-94-6469-372-0 Last accessed online: https://bit.ly/HILA_Drachsler

[16] Macfadyen, L. P., Lockyer, L., & Rienties, B. (2020). Learning design and learning analytics: Snapshot 2020. Journal of Learning Analytics, 7(3), 6-12. https://doi.org/10.18608/jla.2020.73.2

[17] Tsai, Y. -S., Moreno-Marcos, P. M., Jivet, I., Scheffel, M., Tammets, K., Kollom, K., & Gašević, D. (2018). The SHEILA framework: Informing institutional strategies and policy processes of learning analytics. Journal of Learning Analytics, 5(3), 5-20. https://doi.org/10.18608/jla.2018.53.2

[18] Schmitz, M., Scheffel, M., Bemelmans, R., & Drachsler, H. (2022). FoLA 2--A Method for Co-Creating Learning Analytics-Supported Learning Design. Journal of Learning Analytics, 9(2), 265-281. https://doi.org/10.18608/jla.2022.7643

[19] Scheffel, M., Schmitz, M., van Hooijdonk, J., van Limbeek, E., Kockelkoren, C., Joppe, D., & Drachsler, H. (2021). The design cycle for education (DC4E). DELFI 2021.

[20] B. Rienties, C. Herodotou, T. Olney, M. Schencks and A. Boroowa, "Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers," International Review of Research in Open and Distributed Learning, vol. 19, 2018. https://doi.org/10.19173/irrodl.v19i5.3493

[21] L. Ali, M. Asadi, D. Gašević, J. Jovanović and M. Hatala, "Factors influencing beliefs for adoption of a learning analytics tool: An empirical study," Computers & Education, vol. 62, p. 130-148, 2013. https://doi.org/10.1016/j.compedu.2012.10.023

[22] Scheffel, M., Niemann, K., & Jivet, I. (2017). The evaluation framework for learning analytics. Heerlen, The Netherlands: Open Universiteit.

[23] A. Mavroudi, S. Papadakis and I. Ioannou, "Teachers' Views Regarding Learning Analytics Usage Based on the Technology Acceptance Model," TechTrends, p. 1-10, 2021. https://doi.org/10.1007/s11528-020-00580-7

[24] V. Venkatesh, J. Y. L. Thong and X. Xu, "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology," MIS quarterly, p. 157-178, 2012. https://doi.org/10.2307/41410412

[25] V. Venkatesh, M. G. Morris, G. B. Davis and F. D. Davis, "User acceptance of

information technology: Toward a unified view," MIS quarterly, p. 425-478, 2003.
https://doi.org/10.2307/30036540

[26] K. Tamilmani, N. P. Rana, S. F. Wamba and R. Dwivedi, "The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation," International Journal of Information Management, vol. 57, p. 102269, 2021. [31] D. W. Shaffer, Quantitative ethnography, Lulu. com, 2017. https://doi.org/10.1016/j.ijinfomgt.2020.102269

[27] T. Zhou, Y. Lu and B. Wang, "Integrating TTF and UTAUT to explain mobile banking user adoption," Computers in human behavior, vol. 26, p. 760-767, 2010.
https://doi.org/10.1016/j.chb.2010.01.013

[28] P. R. Warshaw and F. D. Davis, "Disentangling behavioral intention and behavioral expectation," Journal of experimental social psychology, vol. 21, p. 213-228, 1985. https://doi.org/10.1016/0022-1031(85)90017-4

[29] A. F. Agudo-Peregrina, A. Hernández-García and F. J. Pascual-Miguel, "Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning," Computers in Human Behavior, vol. 34, p. 301-314, 2014. https://doi.org/10.1016/j.chb.2013.10.035

[30] Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. Journal of advanced nursing, 62(1), 107-115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

[31] Hsieh, H. F., & Shannon, S. E. (2005). Three approaches to qualitative content analysis. Qualitative health research, 15(9), 1277-1288.
https://doi.org/10.1177/1049732305276687

[32] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative research in psychology, 3(2), 77-101.
https://doi.org/10.1191/1478088706qp063oa

[33] Guest, G., MacQueen, K. M., & Namey, E. E. (2011). Applied thematic analysis. sage publications. https://doi.org/10.4135/9781483384436

[34] Gee, J. P. (2014). An introduction to discourse analysis: Theory and method. Routledge. https://doi.org/10.4324/9781315819679

[35] Potter, J., & Wetherell, M. (1987). Discourse and social psychology: Beyond attitudes and behaviour. Sage Publications, Inc.

[36] Thornberg, R., Perhamus, L., & Charmaz, K. (2014). Grounded theory. Handbook of research methods in early childhood education: Research methodologies, 1, 405-439.

[37] Glaser, B. G., & Strauss, A. L. (2017). Discovery of grounded theory: Strategies for qualitative research. Routledge. https://doi.org/10.4324/9780203793206

[38] Ten Have, P. (2007). Doing conversation analysis. Doing Conversation Analysis, 1-264. https://doi.org/10.4135/9781849208895

[39] Heritage, J., Sidnell, J., & Stivers, T. (2013). The handbook of conversation analysis. https://doi.org/10.1002/9781118325001

[40] D. W. Shaffer, Quantitative ethnography, Lulu. com, 2017.

[41] D. W. Shaffer, W. Collier and A. R. Ruis, "A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data," Journal of Learning Analytics, vol. 3, p. 9-45, 2016.
https://doi.org/10.18608/jla.2016.33.3

[42] D. Shaffer and A. Ruis, "Epistemic network analysis: A worked example of theory-based learning analytics," Handbook of learning analytics, 2017.
https://doi.org/10.18608/hla17.015

[43] S. Zhang, Q. Liu and Z. Cai, "Exploring primary school teachers' technological

pedagogical content knowledge (TPACK) in online collaborative discourse: An epistemic network analysis," British Journal of Educational Technology, vol. 50, p. 3437-3455, 2019. https://doi.org/10.1111/bjet.12751

[44] M. Koehler and P. Mishra, "What is technological pedagogical content knowledge (TPACK)?," Contemporary issues in technology and teacher education, vol. 9, p. 60-70, 2009.

[45] S. Cox and C. R. Graham, "Using an elaborated model of the TPACK framework to analyze and depict teacher knowledge," TechTrends, vol. 53, p. 60-69, 2009.

https://doi.org/10.1007/s11528-009-0327-1

[46] D. M. Bressler, A. M. Bodzin, B. Eagan and S. Tabatabai, "Using epistemic network analysis to examine discourse and scientific practice during a collaborative game," Journal of Science Education and Technology, vol. 28, p. 553-566, 2019. https://doi.org/10.1007/s10956-019-09786-8

[47] D. W. Shaffer, "Epistemic frames for epistemic games," Computers & education, vol. 46, p. 223-234, 2006. https://doi.org/10.1016/j.compedu.2005.11.003

[48] J. Hulland, "Use of partial least squares (PLS) in strategic management research: A review of four recent studies," Strategic management journal, vol. 20, p. 195-204, 1999. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7

[49] J. Henseler, C. M. Ringle and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," Journal of the academy of marketing science, vol. 43, p. 115-135, 2015.

https://doi.org/10.1007/s11747-014-0403-8

[50] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," Journal of the academy of marketing science, vol. 16, p. 74-94, 1988.

https://doi.org/10.1007/BF02723327

[51] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," Journal of marketing research, vol. 18, p. 39-50, 1981. https://doi.org/10.1177/002224378101800104

[52] D. Gefen, D. Straub and M.-C. Boudreau, "Structural equation modeling and regression: Guidelines for research practice," Communications of the association for information systems, vol. 4, p. 7, 2000. https://doi.org/10.17705/1CAIS.00407

[53] Marquart, Honojosa, Swiecki, Eagan and D. W. Schaffer, Epistemic Network Analysis (Version 1.7.0) [Software].

[54] A. L. Siebert-Evenstone, G. A. Irgens, W. Collier, Z. Swiecki, A. R. Ruis and D. W. Shaffer, "In search of conversational grain size: modelling semantic structure using moving stanza windows.," Journal of Learning Analytics, vol. 4, p. 123-139, 2017. https://doi.org/10.18608/jla.2017.43.7

[55] G. Arastoopour, N. C. Chesler, D. W. Shaffer and Z. Swiecki, "Epistemic network analysis as a tool for engineering design assessment," in 2015 ASEE Annual Conference & Exposition, 2015.

[56] S. Sullivan, C. Warner-Hillard, B. Eagan, R. J. Thompson, A. R. Ruis, K. Haines, C. M. Pugh, D. W. Shaffer and H. S. Jung, "Using epistemic network analysis to identify targets for educational interventions in trauma team communication," Surgery, vol. 163, p. 938-943, 2018. https://doi.org/10.1016/j.surg.2017.11.009

[57] S. McKenney and Y. Mor, "Supporting teachers in data-informed educational design," British journal of educational technology, vol. 46, p. 265-279, 2015.

https://doi.org/10.1111/bjet.12262

[58] A. F. Wise, Y. Zhao and S. N. Hausknecht, "Learning analytics for online discussions: Embedded and extracted approaches.," Journal of Learning Analytics, vol. 1, p. 48-71, 2014. https://doi.org/10.18608/jla.2014.12.4