Mapping Engagement Dynamics in Online Adult Education

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Abstract

In Sweden, 95% of adult learners at the compulsory school level and 47% at the upper secondary level were foreign-born in 2022. This explains why language learning is in high demand among migrants and why the contribution of Municipal Adult Education in improving employability and fostering inclusivity is paramount. Teachers are expected to design learning activities across synchronous and asynchronous modes to ensure that learners engage. While there is a general call for more research on student engagement in various online learning contexts there are also specific and significant gaps in research in relation to the design, implementation, and evaluation of Learning Sequences and empirical studies of adult education, such as the didactic practices of adult education teachers. This study seeks to contribute by investigating how educational modes influence learner engagement and can inform future learning designs. Over a nine-month period, observations (n=34), were made in both asynchronous (n=25) and synchronous (n=9) modes of second language learning settings, examining teachers' instructional designs. Analysing how designs facilitate learner engagement across learning sequences through Sequential Pattern Mining and Social Network Analysis, the findings show that engagement is significantly influenced by both learning design and mode of delivery. The findings suggest that a combined approach, merging synchronous and asynchronous modes, could significantly enhance learning outcomes. Notably, cognitive engagement—traditionally associated with the self-directed and autonomous nature of asynchronous learning—emerges as a vital component with a broader function. Learning activities characterised by cognitive stimulation frequently precede those fostering other engagement types (behavioural, social, emotional), unveiling cognitive engagement's pivotal role not merely in individual learning but also as a bridging mechanism. This bridging capacity of cognitive engagement underlines its importance in the holistic facilitation of engagement, suggesting that online learning designs must go beyond individual learning to incorporate this mediating role. This insight not only advances our understanding of engagement dynamics in online adult education but also emphasises the critical need for learning designs that leverage cognitive engagement to unify various forms of engagement, thereby optimising the educational experience for adult learners.

Keywords: *Learning sequences, Engagement, Synchronous, Asynchronous, Municipal Adult Education, Sequential Pattern Mining*

1 Introduction

As learning moves online, learners and teachers are potential users of both physical and digital technologies. The rapid development of emerging technologies can, and is likely to, transform how education is distributed and how teaching and learning are undertaken [1]. However, the synchronous and asynchronous modes of online education each come with their own conditions: both have their advantages, such as active interaction in synchronous modes [2] and flexible pacing in the asynchronous [3] as well as challenges, such as learners feeling isolated (in asynchronous mode) [4]. While synchronous interaction is accessible to anyone with internet connectivity and a device, asynchronous learning necessitates a higher level of independent study, owing to limited real-time support. While the emergence of artificial intelligence solutions offers a variety of intelligent technologies to assist second language learners with automated feedback, personalised responses, and assessment, and through diagnosing learner input [1]. While the emergence of artificial intelligence solutions offers a variety of intelligent technologies for assisting second language learners by providing automated feedback, personalised responses, assessments, and diagnosing learner input [1]. Municipal Adult Education (MAE) in Sweden has received comparatively limited financial resources, particularly when compared to other forms of schooling on a per capita basis, necessitating most adult learners to provide their own digital devices for participation [5]. Thus, teachers must design learning activities using the means available, to engage learners by efficiently balancing synchronous and asynchronous modes to ensure that learners engage (Ifenthaler et al., 2018). While there is a general call for more research on student engagement in various online learning contexts so that relevant data can be accumulated [6] there are also specific and significant gaps in research in relation to the design, implementation, and evaluation of Learning Sequences (LS) [7] and didactic practices of adult education teachers [5]. Addressing these gaps can provide a comprehensive understanding of engagement dynamics in online adult education. To address this gap, longitudinal qualitative data was collected to provide a nuanced view of engagement dynamics in intended learning designs across synchronous and asynchronous modes. Data were analysed using statistical methods, Sequential Pattern Mining (SPM) and Social Network Analysis (SNA). To our knowledge, no previous research has explored engagement dynamics and LS in second language learning designs across synchronous and asynchronous modes in MAE. Against this background an overarching research question was raised: How do synchronous and asynchronous modes in second language learning designs in MAE influence the engagement dynamics, and what implications do these variations have for optimising learner engagement and learning design? To answer this, the following sub-questions were raised:

1. How do the distribution and duration of activities occur in synchronous and asynchronous modes of in second language learning designs in adult education?
2. How do variations in activities and the occurrence of learning sequences influence engagement dynamics in second language learning designs in adult education?
3. How do Social Network Analyses elucidate the connections between different learning sequences in synchronous and asynchronous learning environments, and what does this reveal about the centrality of certain activities in second language learning designs in adult education?

2 Background

2.1 Learning design and learning sequences

In this study, distance education is approached. Since earlier definitions of distance education are no longer valid [8]; the terms synchronous and asynchronous modes of education are used. These are subsumed under distance education and convey separate conditions for learning, learning design, and educational distribution. A learning design (LD) is referred to as "the documented design and sequencing of teaching practice, and how together these may serve to improve understanding and evaluation of teaching intent and learner activity” [9:1440]. LDs emerge from teacher planning and pedagogical intent [9]. A LD is composed of various Learning Sequences (LS), each involving a series of activities and resources [10] strategically chosen to foster learner engagement [11]. However, the selection and effectiveness of these sequences vary significantly between synchronous and asynchronous educational modes. For instance, in asynchronous modes, LS are part of well-structured LDs, emphasising pre-planned activities [7]. In contrast, synchronous modes feature LS that are more fluid, allowing educators to dynamically adapt in response to real-time interactions and events [12] through improvisation and co-creation of learning using the learning design as a framework [7]. Understanding the composition of LDs from LS in both synchronous and asynchronous modes is crucial. This insight will guide practitioners in crafting LDs that effectively balance the inherent strengths of each mode to optimise learning outcomes. Teachers enter the classroom with an idea of the LDs meant to take place, that align with the curricula and learning goals. The LDs can then be broken down into learning sequences. Sequencing information and actions is fundamental to human beings [13] and it is closely related to teachers’ intent when designing learning. Thus, LDs consist of learning sequences (LSs) which in turn comprises a series of activities. In other words, LSs are viewed as patterns of activities [14, 15]. [14] define a LS as "an ordered use of learning processes" [14: 612]. Even if research has identified common or shared LDs [16] one cannot exclude that there can be a discrepancy between intended designs and how the LDs are played out. This does not mean that intended designs cannot be realised. For example, in their seminal work on intentional LSs [15] designed a series of activities positioned (left to right) A to D. Their respondents were exposed to ten successive repetitions through a ten-item sequence per block. [15] found that, in comparison to others, their respondents made fewer mistakes and solved the task faster, suggesting that familiarity and experience may bolster productivity and learning. Exploring the nature of LS [14] found that LSs may expand and contract as items are added or deleted to the learning activity and that such evolution of the LS may be intentional or unintentional. [14] suggested LS may evolve over time and with repeated use. With the increase in online education [17] digital resources, such as, educational games [18] or intelligent educational systems and agents that curate materials and scaffold learning paths, understanding LSs is paramount, as sequences of actions determine the execution of the algorithm [19]. [20] used sequence mining, and combined multiple data sources, to analysis the temporal nature of learning actions, and their transitions dynamics. While identifying university level student strategies and their transitions, they also argue that network analysis, could be suitable when approaching relational aspects in the data and include more than just trace data to provide a fuller picture. Turning to adult education, and teachers' perspective, another study found that generated insights could indeed inform development of designs, which in turn led to improve learner performance [21]. However, analysing LS from all learners' perspectives may be challenging, as teachers may offer compulsory or optional anytime, anywhere learning in parallel with distributed didactic units in the Learning Management System (LMS) [22]. Furthermore, because adult learners may have developed a higher ability for self-directed learning (than younger learners), teachers can expect a larger capacity and expectation regarding design variations [23]. The abilities may include being able to participate in online simulations, collaboration, video recording and independent orientation across different online and physical spaces. Thus, exploring LDs using mixed methods can be suitable [17, 24]. In order to learn new ways to learn as adults [23, 25] adults need to undergo a process of reorientation to learning. Adult educators need to design, scaffold, and structure intentional activities and LS across multiple educational modes to cater to these learners. Emerging research has suggested that combining both modes may increase learner engagement [26]. Recognising the distinct conditions for each mode is essential, and prioritizing online engagement is pivotal for addressing dropout rates in online learning [27]. Hence, knowing how to engage learners across modes is critical, as engagement is key to increase retention, success rates and wellbeing [28, 29].

2.2 Engagement

Here, engagement is conceptualised as four-dimensional with a behavioural, a cognitive dimension, an emotional, and a social [28]. A key component of behavioural engagement is actions that proactively contribute to learning [28]. Additionally, cognitive engagement involves concentration and self-regulation, such as planning, orienting, and evaluating one's work [29]. Cognitive engagement is dominant in assimilative activities, as these rely on the passive absorption of information [30] assimilative learning can, for example, include listening, observing and silent reading. Linking learning design to engagement [30] found that assimilative learning activities were negatively correlated with grades. Social engagement entails interactions between learners, teachers, tools, and resources [31]. Arousal, curiosity, and self-efficacy are all indicators of emotional engagement [28, 29]. The interconnectedness of learning sequences and engagement in the educational sphere has been established [32].Carefully designed LSs can be a cornerstone in fostering an environment where engagement can thrive in its multifaceted dimensions, seamlessly bridging synchronous and asynchronous modes of learning. Due to its long tradition of plain reading courses and limited interaction [8] asynchronous education is widely believed to be synonymous with self-directed learning [33]. Indeed, research has found that in asynchronous learning, the designs relied mostly on stimulating cognitive engagement [28]. In addition, design for engagement should be prioritised as engaged learners are those who succeed academically [29] why exploring engagement dynamics and learning sequences across synchronous and asynchronous modes becomes critical.

3 Method

3.1 Context and Participants

Situated within a longitudinal case study methodology [34] the study engaged MAE teachers (n=20). Observing and interviewing each teacher individually allowed collection of their learning design approaches. The teachers had 4 to 43 years (median: 16 years) of teaching experience. All teachers had access to internet, a LMS, and a laptop. All teachers taught courses in either English as a Second Language (ESL) or Swedish as a Second Language (SSL) in synchronous or asynchronous modes. These courses were structured across levels 1 to 4, with each level offering increasingly advanced language training covering all fundamental skills. While ESL courses correspond to the B1.1 level of the Common European Framework of Reference for Languages (CEFR), SSL courses at levels 1 to 4 do not have a direct CEFR equivalent. Following the principals' approvals, a purposive sampling strategy was employed [35].

3.2 Data collection and analysis

Observations (n=34) of asynchronous (n=25) and synchronous (n=9) learning situations modes were collated across nine months, during 2021-2022, using a structured observation schema. Each observation was manually documented in MS Excel (ver. 16.76) adopting a one activity per row, with the categories: observation no, respondent, time, duration, activity, description, and comments. For the asynchronous modes a 'talk-aloud' method was used [36]. The teachers simulated a typical learner in their class, actively articulating their thoughts and decisions as they navigated their course. By demonstrating their points within digital environments, teachers described and explored their intended design in detail. SPM was used to uncover complex engagement patterns within qualitative learner data [36]. An SPM approach facilitates the analysis of intricate data gathered during learner interactions with their learning environments and peers. The goal of SPM is to identify patterns in activities that may form a sequence (Knight et al., 2017 [20]. Traditionally applied to quantitative LMS trace data, our study's novel application of SPM specifically harnessed the rich detail from qualitatively gathered data, intertwining activity frequency and types with narrative teacher descriptions and observations [37]. A hypothesis was formed that this qualitative approach, albeit time-intensive, could yield richer insights into the dynamics of engagement. The data set (502 manually coded rows) was analysed using statistical analysis and SPM [37]. SPSS (ver. 27) was used to perform Levene's test, ANOVA, and a Games-Howell post-hoc test. The data analysis for Fig. 2 and 3 was executed using Python (ver. 3.8.10). Distinct learning sequences was the unit of analysis [38]. All activities in a LS are exclusive to that sequence, and do not form part of another LS. Data were further analysed to ensure the extracted LS contained units of meaning. Overlaps were removed. LS were then mapped with their responding teacher description and observation comments. The descriptions were used to identify common core characteristics of the recurring LSs to inform shared characteristics of the LSs. Finally, SNA was conducted to explore the relational data in a network structure. It provides the structural properties of a network by visualising a pair of actors [39].The SNA graph (see Fig. 4) visually represents the activities and their respective transitions, offering insights into the centrality of certain activities within the second language LDs. Based on the theories posited by [39] the node degree analysis was used to identify the connectivity levels of different activities within the network, highlighting prominent activities and their respective roles in fostering engagement, and betweenness centrality was analysed as a measure to identify the most influential nodes in a network, based on their role in acting as bridges between other nodes in the network [40].

4 Result

4.1 The distribution and duration of activities across synchronous and asynchronous modes

To explore the distribution and duration of activities across synchronous and asynchronous modes in adult education (research question 1), all activities and their categorisation (see Fig. 2) and the spread of activities across modes were analysed.

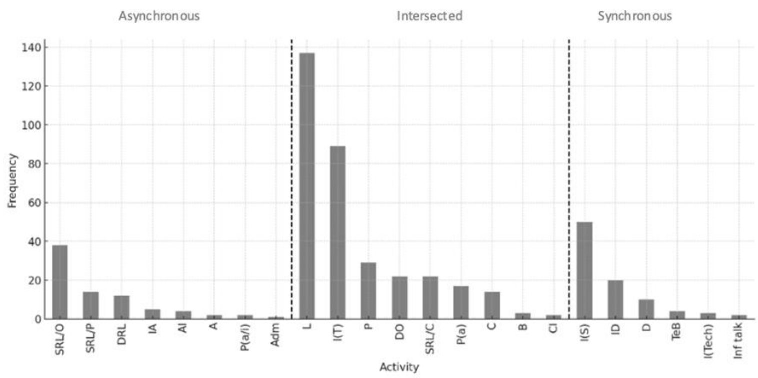

Fig. 1 Distribution of modes and activities across modes

Fig. 2 reflects the distribution of the 23 inductively identified activities. 17 out of 23 activities were linked to an engagement dimension. (see OSF Appendix A). Fig. 2 includes entities such as technology breakdown (TeB), administration (Adm), and informal talk (Inf talk) outside the learning situation (here before class). Taken together, the modes show distinct trends. Synchronous learning involves interactive and assimilative activities that foster cognitive and social engagement with activities like learner-initiated interaction I(S), (9.96% of the activities) and discussion (D) (1.99% of the activities) being characteristics of the unique collaboration style. However, there is also a frequent amount of idle time (ID) (3.98% of the activities) when the class waits for learners to re-join moving in and out of breakout rooms. In contrast, the asynchronous mode tends to be uniform in the types of activities, displaying characteristics linked to self-regulated learning, particularly SRL/O and SRL/P, which constitute 13.88% and 8.92% of the total activities, respectively. This may indicate a need to diversify the learning experience, that do not rely so heavily on cognitive engagement only. Some activities were (naturally) planned in both modes, such as breaks and sharing course information. Considering the influence of technology breakdowns (TeB), administration (Adm), and informal talks (Inf Talk) on the learning environment, results show that neither of these "non-learning" activities (17-23) were prominent, for example, technology breakdowns did occur in synchronous settings but were both rare and unintended activity. Therefore, learning activities that were linked to engagement were explored.

4.2 Variations in activities and LS as reflectors of engagement dynamics

To explore how variations in activities and occurrence of LS influence engagement dynamics in adult education (research question 2), an ANOVA test, and a post hoc test was conducted and the data was analysed for patterns using SPM.

Table 1 ANOVA test

Mode	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	29,784	3	9,928	57,884	0,000
Within Groups	77,868	454	0,172		
Total	107,653	457			

Table 2 Games-Howell Post-hoc test

Engagement dimension	Engagement dimension	Mean Diff.	Std. Err	Sig.	95% Confidence Interval Low. Bound	Upp. Bound
Behavioural	Cognitive	21.57*	4.31	0,000	10.10	33.04
	Emotional	-2,91	8.46	0,986	-25.44	19.61
	Social	22.79*	4.29	0,000	11.38	34.20
Cognitive	Behavioural	-21.57*	4.31	0,000	-33.04	-10.11
	Emotional	-24.49*	7.34	0,012	-44.51	-4.46
	Social	1.22	0.90	0,525	-1.09	3.53
Emotional	Behavioural	2.91	8.46	0,986	-19.61	25.44
	Cognitive	24.49*	7.34	0,012	4.46	44.52
	Social	25.70*	7.33	0,008	5.70	45.71
Social	Behavioural	-22.79*	4.29	0,000	-34.20	-11.38
	Cognitive	-1.22	0.90	0,525	-3.53	1.10
	Emotional	-25.70*	7.33	0,008	-45.70	-5.70

*. The mean difference is significant at the 0.05 level.

The data was tested for homogeneity of variances across the modes using Levene's test to determine the appropriate statistical methods. The test yielded the following results: based on mean (statistic = 323.160, $p < 0.0001$), based on median (statistic = 30.438, $p < 0.0001$), based on median with adjusted df (statistic = 30.438, $p < 0.0001$), and based on trimmed mean (statistic = 322.138, $p < 0.0001$). Consequently, Welch's ANOVA (Welch, 1951) was selected for further analysis as it accommodates unequal variances. The ANOVA (Table 1) indicates a statistically significant difference in the durations of activities across the different modes of learning (synchronous and asynchronous). There was a statistically significant difference in the activity durations across the different modes ($F(3, 454) = 57.884$, $p < 0.0001$). This substantial F value further substantiates this finding. The synchronous and asynchronous modes were explored using pairwise comparisons (see Table 2). Duration was used as the dependent variable and engagement dimensions as independent. Table 2 reveals a disparity between cognitive and emotional dimensions, in the asynchronous mode, denoted by a mean difference of 24.49 ($p = 0.012$). This suggests that activities within the emotional dimension. The two dominate activities in this dataset for emotional engagement is assessment (as linked to arousal, anxiety) and was the activity, creative production (which was rare). Thus, assessments (mainly) tend to be shorter, possibly reflecting a preference for shorter assessments. In contrast, the synchronous mode indicates a difference in the duration of behavioural and emotional activities, and cognitive and emotional activities, as denoted by a mean difference of -25.70 ($p = 0.008$) and -24.49 ($p = 0.012$) respectively. This signals that long assessments are more common in the synchronous mode.

Furthermore, the results show discrepancy in the duration between emotional and social activities, with a mean difference of -25.70 ($p = 0.008$). This implies that social activities in synchronous setups are relatively concise, likely focusing on targeted interactive or collaborative tasks that don't require extended time frames. These findings delineate the distinctive engagement dynamics in asynchronous and synchronous learning environments, highlighting the diversity in engagement levels within these settings. Conducting SPM, LS were matched with distribution and frequency. Exploring the data several key insights emerge regarding engagement dynamics in adult education settings based on the engagement sequences. The 'Cog-Cog-Cog-Cog' sequence, observable in learning patterns 'SRL/O-L-SRL/P-L' and 'L-L-L-L', primarily indicates a learner-centric approach where individuals or groups actively select tasks to initiate their learning journey, hinting at a structured yet autonomous learning process. Sometimes learners use different online spaces. This is referred to as a digital relocation (DRL). A different aspect of learning dynamics is revealed by the 'Cog-Cog-NonE-Beh' sequence, evident in the 'L-L-DRL-P' and 'L-L-DRL-P(a)' patterns. This sequence reflects a transition between spaces, and in this LS a shift from cognitive to behavioural engagement, where resources are used to stimulate higher-order thinking, fostering deeper engagement and critical analysis. The 'Soc-Cog-Soc-Cog' and 'Cog-Soc-Cog-Soc' sequences, seen in patterns such as 'I(T)-L-I(T)-L' and 'L-I(T)-L-I(T)', illustrate a balanced interplay between social and cognitive engagement. Here, the learning environment appears to be characterized by teacher-guided instruction and interaction-focused information dissemination, fostering a collaborative learning atmosphere where students are encouraged to interact and engage with the content and their peers. Here, social, and cognitive engagement is facilitated, encouraging learners to participate in discussions actively and promoting an interactive and communicative learning environment. In addition to this, sequences such as 'Soc-Soc-Cog-Soc' and 'Soc-Soc-Soc-Soc', evident in patterns such as 'I(T)-I(T)-L-I(S)' and 'I(S)-I(T)-I(S)-I(T)' are indicative of a strong social focus. These sequences combine active learning with teacher-led discussions and student-engagement dialogues. While these LS may stimulate a communicative learning setting, there is a potential risk of not facilitating in-depth learning due to the brevity of interactions, necessitating careful consideration between facilitating social and cognitive engagement. While Fig. 2 and 3 indicated an increased tendency for cognitive engagement in the asynchronous mode. Combining these findings with SNA enables a comprehensive analysis of the learning network's structure and dynamics.

4.3 Social Network Analyses connections between learning sequences

Finally, (and responding to research question 3), an SNA was conducted to explore the connections between different activities in synchronous and asynchronous learning environments and what this reveal about the centrality of certain activities in second language learning design in adult education. The degree of centrality indicates an actor's connectivity or integration level within the network structure under study [39]. In the synchronous mode, teacher-led (I(T)) and assimilative learning (L) activities are central nodes in the network, as evidenced by their high node strengths (151 and 163, respectively), signalling their significant role in the learning sequence.

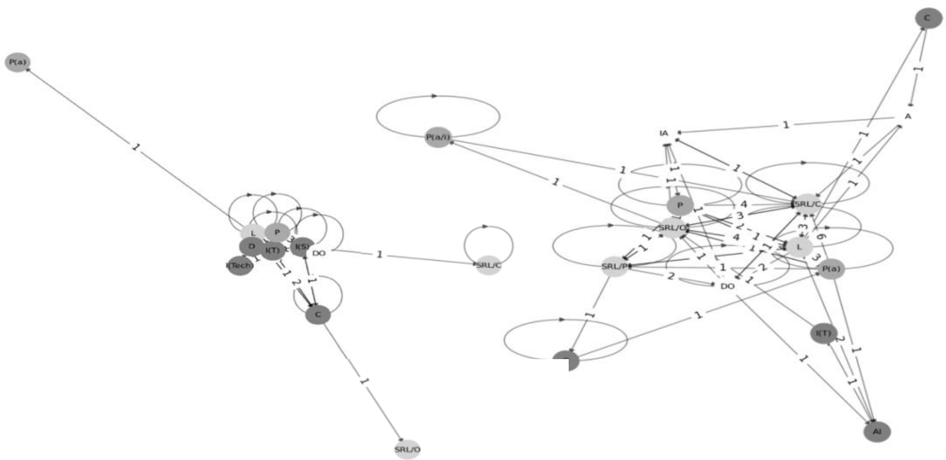

Fig. 2 Social Network Analysis (left synchronous, right a synchronous mode)

Asynchronously, orientation (SRL/O) and assimilative learning (L) dominate engagement node strengths (with 61 and 88, respectively). An asynchronous learning pattern like this illustrates the often, self-regulated nature of the asynchronous learning process, where other activities often precede orientation. Moreover, community detection algorithms categorised these activities into distinct communities, illustrating the closely interconnected clusters of activities in each mode. Betweenness centrality analysis further emphasises the critical role of assimilative learning (L) in the synchronous mode. It acts as a significant bridge in connecting various learning sequences, indicating its vital role in integrating different aspects of learning (Freeman, 1977). Conversely, orientation (SRL/O) serves a similar role in the asynchronous mode, highlighting its function as a recurrent point of return as learners navigate through different learning sequences. Different patterns of centrality in different activities can be observed when comparing both modes. The synchronous mode balances teacher-led, learner-led, and assimilative learning activities, fostering a collaborative and interactive learning environment. In contrast, the asynchronous mode prioritises self-regulated learning activities, with orientation and assimilative learning emerging as central nodes and bridges in the network. It suggests a tendency for asynchronous learning sequences to centre around these activities as learners engage with the learning material at their own pace. Using path analysis, top paths were identified (SRL/O → L → SRL/P → DO → IA → SRL/C, SRL/O → L → SRL/P → DO → SRL/C and SRL/O → L → SRL/P → C → P(a) → SRL/C) these findings, together with the previous analysis, suggest that long recurring LS are more common in asynchronous modes, whereas the synchronous mode offers a larger variety of LS (see Fig. 4). All of the top LS came from asynchronous modules, and they were quite long (six activities), suggesting that teachers designing asynchronous modes are able to vary the learning design and LS within the prevalent (cognitive) engagement dimension.

5 Discussion

[27] noted that learner engagement patterns vary depending on the pedagogy and course duration and [17] concluded that learner profiles are critical to consider. Expanding on these arguments, the results in this study revealed a greater variation of LS across engagement dimensions in the synchronous mode, than in the asynchronous mode, (which on the other hand displayed a greater nuance of activities within each dimension (particularly the cognitive). This is important, as it indicates that pedagogy and duration are not disconnected from the mode of distribution but should be considered alongside for example learner's profile and choice of learning design. Expanding previous research e.g., [6, 27] 23 unique activities were identified, but only about 1/3 were intersected; suggesting that teachers produce certain types of learning designs more easily in each mode, with the social and cognitive engagement dimensions the most prominently supported in asynchronous and synchronous modes respectively. While cognitive-heavy designs have been linked to assimilative practices [30] the SNA results presented demonstrate that LS with cognitive engagement functions as central nodes in the network, frequently follows, or are followed by, a wide variety of other activities. Furthermore, the SNA reveals that some assimilative learning is central to second language LDs across synchronous and asynchronous modes. As such, practitioners must not refrain from assimilative learning activities but ensure to complement them to achieve a balanced approach to learning design, integrating information absorption and interactive discussions while exploring ways to increase behavioural and emotional engagement. Analysis LSs offered nuanced insights into the dynamics of engagement. In synchronous learning environments, a recurring cycle of teacher-led interactions and assimilative learning formed a loop of interaction and content absorption, sometimes coupled with collaborative and practice-based activities. These findings contrast with the traditional view of asynchronous learning, where a view of asynchronous education as self-directed approach prevail. Despite the active involvement of teachers in synchronous sessions, the brevity of these interactions suggests a brisk learning pace or surface learning, potentially limiting the depth of content absorption, stimulation of higher-order thinking and development of self-directedness. While adapted to the learner's scaffolding needs or wants [25] increased flexibility could foster self-regulating abilities, gradually allowing the learners to become more self-directed. It's essential to note that the essence of a LDs lies in how effectively it orchestrates its constituent LSs to create a cohesive and engaging educational journey. In line with previous research [2, 3, 31] the key results highlight a necessity for practitioners to adopt a balanced approach to learning design, intertwining assimilative learning activities with interactive discussions, and exploring avenues to enhance behavioural and emotional engagement. A recommendation is thus that LDs should consider combining both

modes to integrate better and balance information absorption and interactive discussions. [14] results show that the LSs might evolve as teachers incorporate parallel learning activities, cross the barriers of traditional space and place-bound activities by incorporating synchronous elements in an asynchronous course, which opens for a wider adoption of mixed-modal educational distribution. As adult education teachers meet a heterogenous group of learners, and increasingly experiment with asynchronous and synchronous modes of delivery, making informed decisions becomes even more critical when striving to support second language acquisition [7, 19].

6 Conclusion

This study contributes to the blended learning discourse, by offering empirical insights into the teacher intent in learning design that interplay between various engagement dimensions and learning modes. It fosters a deeper understanding of blended learning environments, potentially guiding the development of future learning designs and learning experiences that utilises the strengths of both synchronous and asynchronous engagements.

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