Towards automated assessment of participation and value creation in networked learning

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Abstract

This paper investigates the integration of artificial intelligence (AI) in Massive Open Online Courses (MOOCs) to improve student engagement and learning outcomes. MOOCs have transformed the landscape of online education, offering wide accessibility but at the price of high dropout rates and limited ability to measure student engagement. With MOOCs' expansive user base, it has been difficult until now to move beyond conventional metrics of course completion and quiz scores, which are insufficient for understanding the multifaceted nature of student engagement. The study addresses these challenges through a novel method of applying a large language model (LLM) to develop a more complex and meaningful understanding of student engagement and experiences in MOOCs.

The research is grounded in the networked learning (NL) research tradition by using the Community of Inquiry framework to explore social, cognitive, and teaching presence in online educational environments and automate the assessment of student learning participation. The study focuses on social engagement and interaction, crucial for perceived value creation. Theoretical soundness, data targeting and quality, interpretation benchmarks, and robust data sampling and analysis strategies constitute the foundational pillars of the proposed predictive system. This framework guides the study's approach to address common MOOC issues, such as learner isolation and limited interaction, which are critical factors in students' perceived value and learning.

The methodology involves a dual approach of human and LLM coding, testing the ability of LLMs to replicate human coding accuracy. The study was conducted in a non-massive open online course to test system effectiveness before applying it to larger MOOCs. Analysis indicates that an initial noncomplex LLM model can match human coding performance to 60% reliability, representing a significant step forward in automating qualitative analysis in online education, with potential for enhanced results using more complex LLM modelling.

Key findings show that AI can effectively measure and enhance student engagement in MOOCs. The use of LLMs in coding qualitative data offers a reliable method for understanding student participation, which is vital for improving educational outcomes in online courses. The research highlights the potential of AI in transforming online education by providing deeper insights into student engagement and learning processes.

The study also provides insights into the interplay of AI-measured engagement and learners' value perception, advancing the understanding of networked learning participation and its impact on educational outcomes. Implications extend to curriculum development, pedagogical strategies, and the broader field of online education. Future work includes expanding this methodology to more extensive MOOC environments and incorporating qualitative interviews to enrich the analysis.

Keywords
MOOCs, AI, LLMs, Value Creation, Qualitative Analysis

Introduction

Massive Open Online Courses (MOOCs) have proliferated as democratized platforms for global education, with numbers having reached approximately 180 million users by 2020 alone (Kala & Chaubey, 2023). They offer unprecedented scale and diversity in educational access, thereby enabling lifelong learning and skills development across various disciplines.

However, the sheer volume and diversity of learners within MOOCs complicate the monitoring of individual learning experiences. Commonly used metrics like course completion and quiz scores inadequately capture the multi-faceted nature of student participation and engagement. Research demonstrates that learners benefit from social engagement and interaction with others (Gourlay et al., 2021). A known problem associated with learning in MOOCS, however is that its predominant educational design (see xMOOCs) is geared towards teacher centred design that promotes individual learning with limited feedback and interaction, resulting in learner isolation and early drop out ((Topali et al., 2021). Perceived value creation (Wenger, Trayner & De Laat, 2011) by learners seems to benefit from engaging in networked social learning experiences in MOOCs (Saadatmand & Kumpulainen, 2014). In this paper we explore the relationship between learner presence in MOOCs and value creation. This research paper pioneers the integration of artificial intelligence (AI) with network learning (NL) models to understand and enhance students' participatory experiences in MOOCs, thereby providing an expedited methodology for scalable course diagnostics and targeted interventions.

Background

AI and MOOCs

The advent of MOOCs has revolutionized the landscape of online education, presenting unique challenges and opportunities in tracking student success. The ability to make reliable predictions of student success and failure within just a few weeks of course commencement is not just advantageous but essential for assessing the effective running of MOOCs. Such capabilities facilitate both formative and summative activities, crucial for enhancing learning experiences and academic achievement.

Formative activities involve the provision of timely feedback and intervention strategies, while summative activities pertain to the recording and marking of student progress against predefined outcomes and standards (Bennett, 2011). By predicting student performance early, educators can implement targeted interventions to support students who are at risk of underperforming or dropping out. Accurate prediction models enable a more nuanced and fair assessment of student performance over the course duration. Thus, prediction of student performance has significant implications for both formative and summative intentions and functions within any type of course, inclusive of MOOCs.

For a prediction system to be effective in MOOCs, it must satisfy several critical benchmarks:

- Theoretical soundness: The system should be grounded in robust theoretical frameworks. Given the nature of learner interactions in MOOCs, the perspective of networked learning is particularly relevant. This approach recognizes the interconnectedness and interactivity inherent in MOOC environments (Saadatmand & Kumpulainen, 2014).
- Data targeting and quality: The system must focus on data that credibly links to predictable learner success. This necessitates not only identifying relevant data but also defining and operationalizing the data in ways that are theoretically sound.
- Data interpretation benchmarks: Establishing benchmarks in key categories for interpreting the collected data is vital for consistency and reliability in predictions.
- Robust data sampling and analysis strategy: The strategy for data sampling and analysis must be feasible, useful, accurate, and appropriate (Stufflebeam, 2001). Historically, this evaluation benchmark has posed significant challenges, as development and utilization of effective systems yielding predictively valid interpretations of performance are labour-intensive, particularly within the context of MOOCs.

The emergence of advanced artificial intelligence (AI) technologies, especially large language models, has opened new avenues for developing feasible predictive systems in MOOCs. These AI advancements have the potential to handle the extensive and complex data inherent in MOOCs efficiently and effectively, thereby making the development of such systems practical and scalable.

The project reported on in this paper aims to develop and test a transferable and replicable system for the prediction of student success and failure in MOOCs. The system comprises:

- A theoretically sound framework that underpins the entire predictive model.
- Clearly defined data targets, benchmarks, and a sampling strategy that align with the theoretical framework and practical requirements of MOOC environments.
- The use of a large-language model (LLM) AI to successfully augment human sampling and analysis.

As a feasible proof of concept project, the project is set within a non-massive open, online course, which presents a feasible initial testing of solutions that may then be scaled, applied, and tested within larger counterparts.

Theoretical framework

Networked learning in MOOCs

The concept of networked learning is central to understanding and improving social learning processes within MOOCs. Networked learning, as defined by the Networked Learning Editorial Collective (NLEC, 2021), involves collaborative, cooperative, and collective inquiry and knowledge creation underpinned by trusted relationships, driven by shared challenges, and facilitated by convivial technologies. This framework places emphasis on three interrelated aspects: human interpersonal relationships, technology, and collaboration, which are pivotal in understanding and advancing learning and engagement in knowledge processes.

The project's approach presented in this paper is grounded in the principles of networked learning, emphasizing collaborative and interactive learning experiences within MOOCs. The theoretical underpinnings of the Community of Inquiry (COI) framework informs our networked learning approach and the analysis of results in this project. It uses this framework and AI (by means of large language models) to offer innovative ways to enhance cognitive, teaching, and social presences (Garison & Arbaugh, 2007) in networked learning design.

At the heart of the networked learning design in MOOCs is social presence: Social presence refers to the communal and emotional aspects that contribute to a supportive learning community (Garrison, Anderson, & Archer, 1999). It encapsulates the ability of learners to project themselves socially and emotionally in a community, fostering a sense of belonging, mutual respect, and connectedness.

Cognitive presence, characterized by the extent and depth of information processing and meaning-making activities. Cognitive presence is essential for deep learning and critical thinking, allowing learners to construct and confirm meaning through sustained reflection and discourse.

Teaching Presence: Teaching presence, encompassing the roles of educational design and facilitation, shapes the learning environment in MOOCs. Effective teaching presence ensures that the course design, organization, facilitation, and direction of cognitive and social processes support and enhance learning outcomes.

The COI framework guides the analysis of MOOC data, focusing on how cognitive, teaching, and social presences manifest and interact in the online learning environment. The project aims to identify patterns and insights that can inform strategies for improving student success and engagement in MOOCs.

The COI framework with its focus on cognitive, teaching, and social presences, provides a comprehensive lens for examining and enhancing learning experiences in MOOCs. This project leverages these theoretical insights to develop and test AI-driven approaches for predicting student success, aiming to contribute significantly to the field of online education.

Data analytics

Predictive learning analytics models enable teacher support and intervention to enable learner success by identifying subpopulations within a course obtained from the learning analytics obtained from indicators within the educational design (Pardo et al., 2016). Within the MOOC context there is a strong focus on predicting learner dropout. Predictive learning analytics typically aim to address 1) enrolment, 2) satisfaction, 3) engagement, 4) performance, and 5) at risk learners (Sghir et al., 2023). Common methods of achieving these predictions include mostly clickstream data, using regression and support vector machines. The complexity of the intentions and aims of predictive analytics contrast with the comparative simplicity of the data and applied methods. Thus, there have been calls for future research to include more sophisticated predictions of learner expectations, exploring the prediction of novel outcomes and connections between them (Moreno-Marcos et al., 2019). Until recently, answering this call has proven challenging, given the limits of what can be accomplished in large-enrolment contexts, such as MOOCs. These limitations centre on the feasibility of teachers managing larger, deeper data sets and performing more complex analytical operations, and doing so rapidly enough to allow for using these results to influence the current students within the MOOC. This project leverages recent developments in AI to move beyond these limitations and address this call.

In summary, this project contributes to the field by harnessing the power of AI, particularly large language models, and data analytics in developing a robust, theoretically informed system for predicting student success in MOOCs. This system promises to enhance both formative and summative educational outcomes, thereby significantly impacting the effectiveness of MOOCs in delivering quality education.

Methodology

Research questions

This study addresses two central research questions:

1. RQ1: How can artificial intelligence be utilized to automatically measure a range of student activities and their engagement with the learning experience?
2. RQ2: How does the measurement produced by artificial intelligence correlate to the value perception of learners?

Data sources & collection

Data for this study was sourced from the LIFT platform, which hosts open, online, non-degree-bearing professional development courses, including MOOCS. LIFT is an initiative of the Centre for Change and Complexity in Learning and Education Futures, at the University of South Australia. The typical LIFT learning experience spans five weeks, with an expected participation of two hours per week, although this varies. Participation in these courses is voluntary, reflecting the open format. LIFT captures extensive learning engagement data, from which three primary data pillars were selected for analysis:

1. Click-stream data: Tracking the digital footprints of learners within the platform.
2. Discussion forum data: Focusing on learner discussions and their impact on learning.
3. Value creation data: Correlating learners' activities with their perceived value of the learning experience, in line with our networked learning approach.

*These three data pilla*rs would help us understand the perceived value of learners and their interaction within the learning experience. The value creation survey was embedded within the learning experience at the end of each week and provided learners a way of reflecting on the experience. The discussion forum provided an avenue for learners to connect and engage in a networked learning community. Using the COI framework provided a way to code these discussions. Table 1 shows the theory indicators, the code names and the coded examples from the LIFT discussion forum.

Table 1: Coding relationships and examples

Theory indicators (Garrison & Anderson 2000)	Code	Coded Examples
Sense of puzzlement Information exchange Connecting ideas Apply new ideas	Cognitive presence	*I assume AI is literal hence instructions will be taken as they are given and there may not be the intuitive interpretation of the question to develop the correct product that has been asked by the user.*
Emotions Risk-free expression Encouraging collaboration	Social Presence	*There is definitely a scary aspect to this but also exciting in terms of individual learning.*
Defining and initiating discussion topics Sharing personal meaning Focusing discussion	Teaching Presence	*How will greater use of AI impact social systems (in the class, between student and teacher, in wider society)?*

Means of analysis

This methodology leverages both traditional qualitative coding and innovative AI-driven techniques to explore the potential of artificial intelligence in measuring and enhancing student engagement and learning outcomes in MOOCs (RQ1) and providing insights for RQ2.

Human Coding

Each week of the LIFT learning event consisted of asynchronous discussion forums where learners were encouraged to share their thoughts on the weekly topics. Text data from the discussion forums was analysed using qualitative coding.

A detailed coding book guided the segmentation (sentence level based on full stops) and coding strategy, using the Community of Inquiry coding template (Garrison & Arbaugh, 2007). Segments could receive multiple codes if overlapping themes were identified. To achieve sufficient inter-rater reliability, three researchers initially coded

10% of the data independently, achieving a benchmark Kappa or Chi-square inter-rater reliability of 75%. Subsequently, one researcher continued coding independently.

Automated Coding

The primary objective was to exhibit the effectiveness of LLMs in replicating human-like coding precision and depth. 10% of the text data was analysed using an LLM, with the coding book and exemplars guiding the process. Notably, initial performance was promising but demonstrated a decline in alignment as we tested the LLM beyond the 10% subset of data.

In an effort to address this issue of human-AI coding alignment, a careful reduction from seven coding categories to three categories was performed. These categories were broader, but maintained fidelity to the theoretical framework, the research questions, the established coding book, and human-human intercoding results. This adjustment had the desired effect on reliability. Using three valid, reliable categories, we were able to achieve 60% intercoding reliability between human and LLM coding, using the full dataset. The reduction is valid as it still maintains fidelity to the research questions, given that a non-complex coding structure was performed on a non-complex model.

Results demonstrate the capability of an LMM to closely reflect the performance of human coders, paving the way for opportunities to automate complex and time-sensitive tasks. Typically, models trained with more parameters can interpret the complex nuances of languages and perform better than smaller models (Naveed et al., 2023). Therefore, as we continue to advance the automated coding process, further steps will be taken to refine the LLM using a model trained on larger parameters to boost its performance.
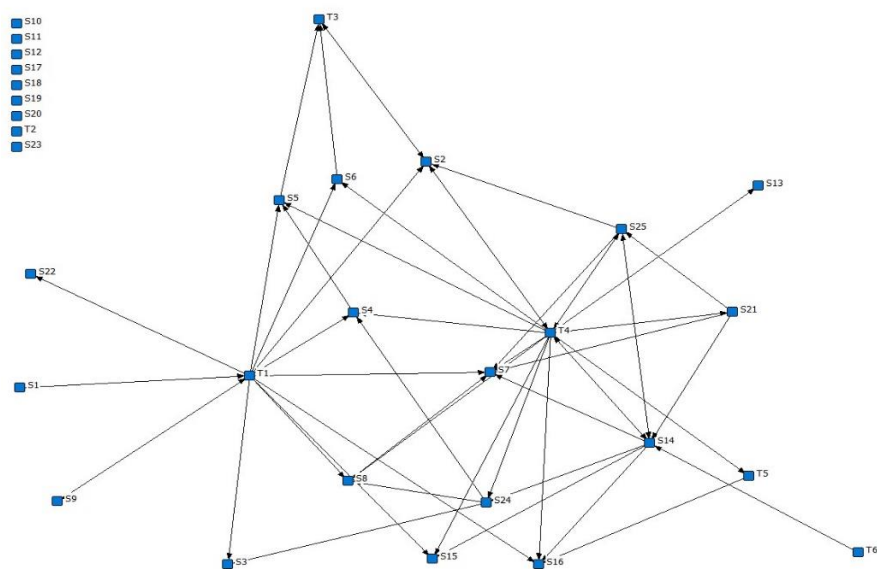
Findings & discussion

Figure 1: Click stream SNA data

Figure 1 represents overall networked learning social interaction amongst the participants based on posting and replying in the weekly discussion forums. Nodes labelled 'S' S-nodes represent messages posted by students. T-nodes are teacher/moderator posts. The list of nodes represented in the top left are participants that did not post any message in the forums over the 5-week course period.

Figure 2 depicts social interaction visualisation based on directed and reciprocal ties. Red ties are reciprocal ties between participants. The blue ties are unidirectional. These occurred most frequently as replies to an original forum post.
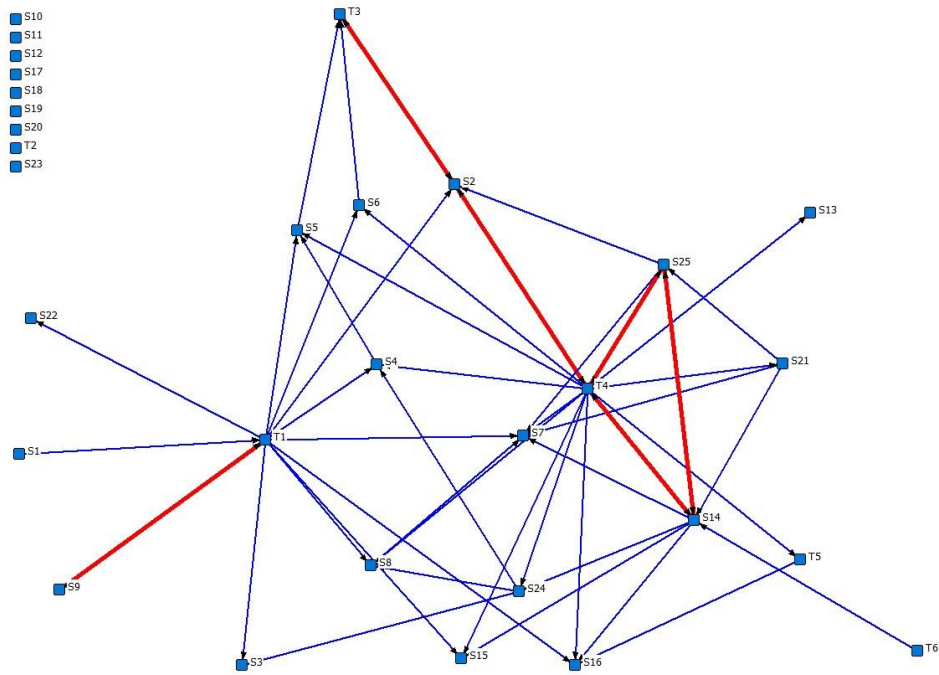
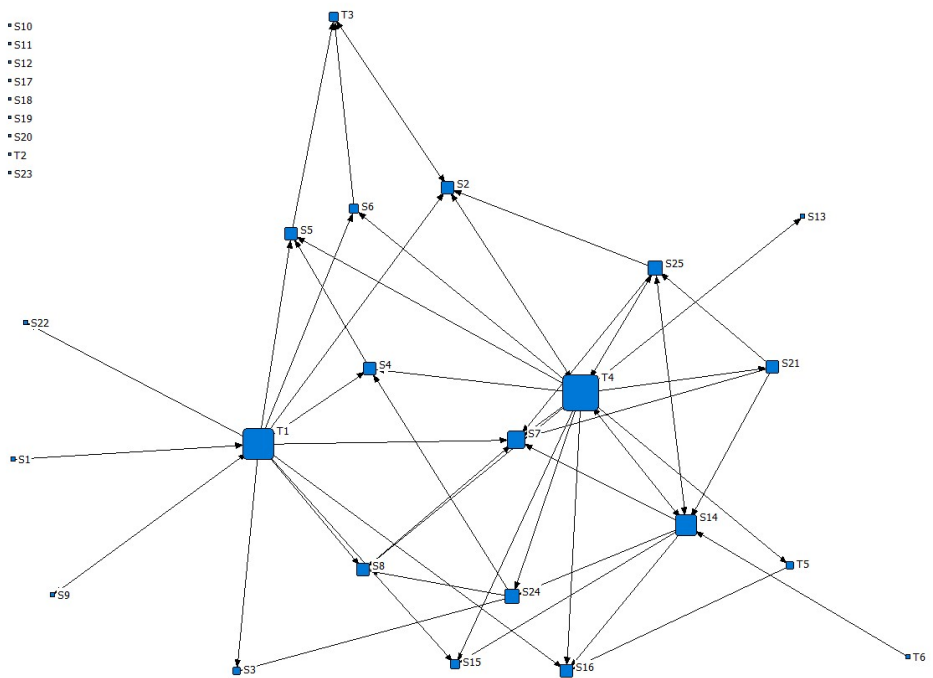**Figure 2: Direct and reciprocal social interaction**

Figure 3: Participant networked relationships

Figure three visualises the participant networked learning relationships based on how they are connected to other learners in their network. The more connections (ingoing and outgoing) the larger the node.

Table 2: Value Creation data

		Value Creation									
		Immediate		*Potential*		*Applied*		*Realised*		*Reframing*	
	N	*Ave*	*StdD*	*Ave*	*StdD*	*Ave*	*StdD*	*Ave*	*StdD.*	*Ave*	*StdD*
W1	18	4.00	1.29	3.26	1.37	4.63	1.21	3.84	1.50	4.16	1.26
W2	11	5.00	0.77	4.73	0.79	5.18	0.87	4.82	0.75	4.55	1.04
W3	11	4.64	1.43	4.70	1.16	5.30	0.67	4.80	0.92	5.00	0.67
W4	9	4.89	0.78	4.44	1.24	5.22	0.83	4.89	0.78	4.78	0.97
W5	6	5.50	0.55	5.33	0.82	5.50	0.55	5.50	0.55	5.50	0.84

Looking at the distribution over the course weeks in Table 1, it is interesting to note that immediate value score is lower and fluctuates when compared to other studies on value creation (Dingyloudi, Strijbos & De Laat, 2019; Guldberg et al., 2021). In general, immediate value tends to get quite a high rating by participants (particularly in the beginning) due to the value experienced when taking part in networked or community events. The immediate presence of fellow members, taking part in conversations and get support from other members adds to the appreciation of immediate value. In comparison reframing value tends to score somewhat lower in other value creation studies (Bertram et al., 2014; Booth & Kellogg, 2015; Patel et al., 2019). The fact this it is quite highly received in this study might have to do with topic of this MOOC and high interest the participants have in AI and AI literacy in relation to their upskilling needs and understanding of the changing impact AI has on life and society.
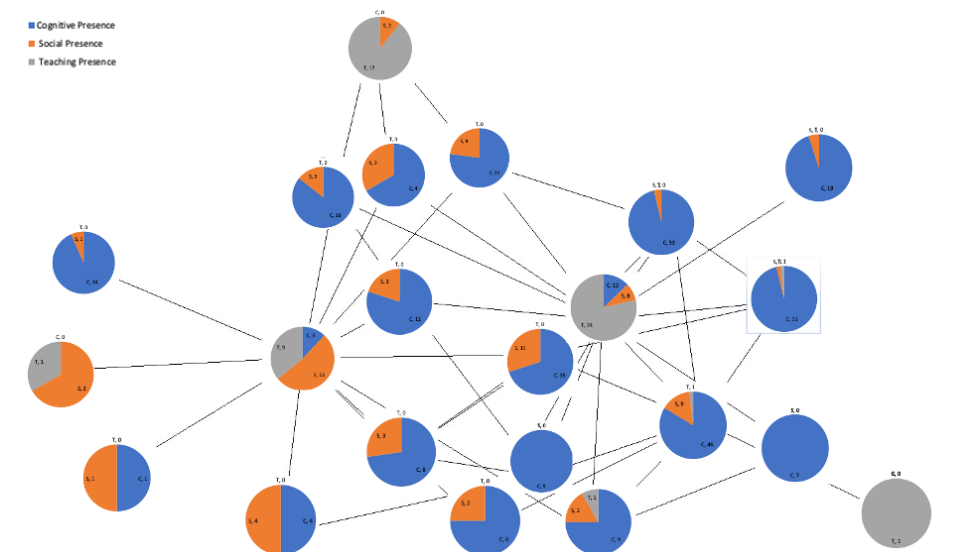

Figure 4: SNA and Presence PIE overlay.

The Presence pie graphs are based on absolute values instead of percentages to avoid skewing the results, given the data sample size. In terms of legend, blue stands for cognitive presence, orange for social presence, and grey for teaching presence.

This research adopts the novel approach of linking value creation data from students with AI-driven coding outcomes, and their networked participation in their online learning community. The ability to link and triangulate data to evaluate students' participation in networked learning enables us to assess students learning from multiple perspectives at once and helps to paint a more complete picture of their engagement and satisfaction. Figure 4 for example suggests an observable trend that students with a lower degree of connections in their network tend to demonstrate a mostly cognitive presence, focussing on learning the content offered in the course. This contrasts with students with a higher degree of connections seeming to be more socially engaged, with concomitant building of group cohesion and investment in a dialogic approach to learning. It is perhaps not surprising to see the general

effect of Teacher nodes having a strong teaching presence in the social network; but is valuable to be able to credibly determine this effect involves encouraging social and cognitive presence in the learning network. Further, teaching presence is not something that is an exclusive domain of the teachers. Some students built a teaching presence, with the aim of coordinating social learning activities that are displayed across the network.

Moving forward with this study, we will overlay individual perceptions of value creation with the results displayed in figure 4 to cross reference active participation with value creation scores. Here the interest will be to find out if certain trends observed in the networked learning activity based on click stream data and content creation can be associated with the kinds of value creation associated with participation. For example, it will be of interest to check if drop out or (increased) nonparticipation is associated with a decline in value creation reports. Hu, Mello, and Gašević (2021) and Taniguchi, Konomi, and Goda (2019) have explored AI coding for classifiers, but our study extends beyond technical aspects by integrating aggregate value creation assessment.

This approach allows us to examine how learners' perceived value creation relates to their position in a network map and offers nuanced insights into their relationship with the community of inquiry. The ability to monitor or predict the relationship between social networked learning (based on presence), their social position in the network or community itself with the value this creates for the learners enables us to observe social learning designs and support mechanisms at scale and test to what extend changes to social learning design in MOOCs have an impact on networked learning participation and value. Equally important, this speaks directly to problem space this research steps into: adopting feasible means of coming to more sophisticated understandings of learners' interactions with the learning engagement, thus opening the possibility for intervention and a shift from teacher-focused to learner focused engagements.

Advancing Nuanced Understanding in MOOCs

Employing a LLM enabled us to achieve a level of detail on students' experience that was previously unattainable in MOOC environments. This was accomplished by using an LLM to engage in rapid coding of a voluminous data set, and attaining sufficient reliability in this coding. Focusing on discussion forums, reducing codes to a broader but valid structure, and setting a threshold of 60% reliability set 'guardrails' for a successful proof-of-concept on the use of LLMs. This aligning with the research objectives and paves the way for future large-scale projects.

Situatedness in Networked Learning Communities

Our study highlights the importance of situatedness in networked learning communities. Addressing critiques of MOOCs, which often centre around teacher-centric designs and limitations in individual learning behaviour, our approach provides a more comprehensive understanding of these learning environments and will help to identify patterns of social engagement and the value participation create for the learners.

Implications for Early Warning Systems and Social Learning Success

The study suggests that the system tested could enable early or ongoing warning signals, potentially reducing dropout rates and enhancing social learning success. This system may translate into educational designs that support self-paced learning while providing necessary scaffolding for retention and success.

Addressing Situated Learning in MOOCs

Situated learning, crucial for promoting social learning (Wegner, Trayner & De Laat, 2011), has been a challenge in MOOCs due to their limited social design. Our system addresses this by coupling Networked Learning as a theoretical framework with framework-relevant data collection and a feasible system of LLM-supported data analysis.

Automated Coding and Predictive Assessment

The introduction of an automated coding mechanism and robust predictive assessment enhances learning behaviour analysis in MOOCs. This advancement is significant in the context of online education, where qualitative data analysis has traditionally been labour-intensive and less feasible on a large scale.

AI-Enhanced Qualitative Analysis in MOOCs

In conclusion, this paper presents ongoing findings from a project that utilizes AI for automating qualitative analysis in a MOOC environment. The networked learning framework underpins this investigation, informing both theoretical constructs and methodological design choices. This integrated approach offers transformative insights into AI's potential in assessing qualitative analysis processes, optimizing student experiences, and

participatory engagement in MOOCs. The implications of this research extend to curriculum application and applied understandings of Networked Learning theory.

Limitations

For our research, the LIFT learning experience we selected is open and online, but not massive. Thus, we may reasonably expect some variances as future research is applied at larger scale. Our decision to start with a smaller scale open online course was intentional, as this afforded us a feasible scope of data to work with, as we developed the proof of concept. Now that proof of concept has been developed, a next iteration of the research will be applied in a large-scale (i.e. 'massive') open, online course context.

A deeper understanding of the participants presence and perceptions of value would be achieved with adding interviews as a component. This step is intended as part of the next iteration of the project. We plan on using critical event recall interviewing technique. This involves providing participants with a prompt, designed to bring them back to a particular point in time and situation in the course, to explain their behaviour and perceptions.

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