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Integrating ICAP theory in learning analytics: A model for evaluating student engagement in online courses

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This paper introduces a conceptual evaluation learning analytics (LA) model developed by Keypath Education and Melbourne Business School to analyse student engagement in an online learning environment. The paper describes how a targeted LA intervention was grounded within the ICAP theory for active learning to identify, visualise and analyse student engagement metrics in a 100% online setting. The architecture of the model, including its design principles and underlying assumptions, are broadly examined against the latest research in educational, LA, and data analytics research. This includes a discussion of our initial phase testing results of captured student data alongside a discussion of key questions and desired study outcomes for the upcoming phase 2 of the data intervention. As a result, this paper provides both specific insights into how we created an evidence based and pedagogically sound evaluation model of online student engagement within a specific suite of asynchronous educational tools, as well as more general and practical insights into how other universities could develop similar approaches to enhance understanding and support of a growing online student population.

Keywords: learning analytics, online learning, ICAP framework, active learning, dashboards, educational data mining

Introduction

Melbourne Business School (MBS) partnered with Keypath Education to develop a 100% online, accelerated Master of Business Administration (MBA) program. The curriculum and teaching content is developed by MBS faculty while a learning designer (LDer), additionally supported by multimedia experts and educational technologists, provide advice and technical expertise on the design and build of the learning for an online environment. The online MBA is designed in a flexible format, to support a student cohort who are working professionals and/or carers and as such have limited time for, or access to, traditional on-campus learning. The content and applied activities are delivered in an asynchronous online environment and supported by live (synchronous) sessions with a facilitator. To help us understand student learning in the online environment, to inform our learning design (LD), and to affect course improvements the teaching and learning team developed a learning analytics (LA) intervention to capture and analyse student engagement data.

A persisting critique within LA research has been its insufficient integration of educational theory into its applications (Lockyer et al., 2013; Mangaroska & Giannakos, 2019; Nguyen & Karunaratne, 2024; Pan et al., 2024) while an additional challenge has been its effective integration into pedagogical practice (Bakharia et al., 2016; Reimann, 2016; Viberg et al., 2018). In responding to these challenges our study started with a theory of learning (the ICAP framework for active learning (Chi & Wylie, 2014)), which was used to inform each step of the model for the LA intervention. We argue that the ICAP framework for active learning with its focus on observable student output may be particularly well suited to environments that rely on the creation of trace data through overt actions like mouse clicks and keyboard entries. In the process of providing the rational for why we selected the ICAP framework as well as describing its application and demonstrating what that meant for data analysis and visualisation, we further synthesise recommendations from the research to adopt a model for the effective integration of LA into pedagogical practice. In the broad sense our work addresses the critique that LA has had minimal influence on teaching practices and learning outcomes (Viberg et al., 2018). In a narrow sense, it provides a step-by-step response to the challenge set by some researchers in LA to develop conceptual and practical frameworks that connect teachers' implemented LD with data and insights derived from LA (Bakharia et al., 2016).

Learning analytics for learning design

A commonly cited definition of LA is: "(*T)he measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*" (Siemens & Long, 2011, p. 34). This definition was provided at the 1st International Conference of Learning Analytics and Knowledge, which also provides a rough date for the establishment of the field. Since its inception, however, a common critique of LA has been a disconnect between the LA intervention itself and established educational theory. A Systematic Literature Review (SLR) by Viberg et al. (2018) concluded that the field of LA remains in a state of development as both a practice and a research area, where descriptive studies and interpretative methods of data collection, as contrasted with theory use and theory generating, are predominant. An additional SLR by Mangaroska and Giannakos (2019), into analytics driven design to enhance learning, found that although various studies have attempted to enhance LD experiences through LA only a handful have grounded their use of LA in established theories and principles from the learning sciences, educational research, technology acceptance, or human-computer interaction. The authors note that in many cases, the theoretical models are implicit, or the studies do not utilise any specific model at all (Mangaroska & Giannakos, 2019). More recent SLRs such as those by Nguyen and Karunaratne (2024) and Pan et al. (2024) have further identified a disconnect between LA and educational theory in research studies.

An additional critique of LA research has been that it does not adequately consider pedagogical context or explore how identifying patterns in trace data can enhance and contribute to more positive teaching and learning experiences. This was identified as a challenge by Lockyer et al. (2013) who posited that the potential of LA would be greatly improved by referencing the LD that outlines the pedagogical intent while Bakharia et al. (2016) argue that there exists a significant knowledge gap for teachers in connecting the insights from LA to the pedagogical actions they design to support student learning. Mangaroska & Giannakos (2019), argued that LD is crucial to any LA intervention as it provides the framework through which data is analysed and learner behaviour is understood (Mangaroska & Giannakos, 2019). They further state that LD defines the educational objectives and pedagogical approaches that educators can reflect upon, make decisions, and implement improvements (Mangaroska & Giannakos, 2019). It is argued that a further misalignment between pedagogical models and LA interventions stems from the discrepancy between data readily captured from system logs and data that holds pedagogical value (Jivet et al., 2018; Mangaroska & Giannakos, 2019). The need for better theoretical grounding has also been identified for the use of learning analytics dashboards (LAD) (Verbert et al., 2020). Verbert et al. (2020) state that dashboards should be better integrated into the learning process and offer actionable suggestions to improve learning.

Active learning and the ICAP framework

LA is not the only educational sub-discipline that struggles to effectively integrate learning science research into practice. van Hout-Wolters et al. (2000) state that active learning is learning in which the student makes decisions about the process of how they learn as well as the extent to which they're challenged to use their mental abilities. Active learning is often contrasted with passive learning, which was based on behaviouristic principles that saw learning as an input-output model in which students learned automatically based on environmental stimuli (Bandura, 2001). It is now generally accepted that passive learning is not the optimal way to learn and according to Scardamalia and Bereiter (2006), much of the effort within education during the 20th century was a move from this transmission model of learning to what is now generally called active learning. However, despite extensive research in the learning sciences that has yielded numerous insights into active learning, the application of these findings in classroom practices by teachers remains limited (Chi, 2021). Chi (2021) argues that despite decades of laboratory research, a gap between research and practice persists that reveals a pressing need for a comprehensive theory of active learning that can offer a coherent interpretation of various educational approaches, and their relative benefits.

The ICAP (Interactive, Constructive, Active, Passive) framework for active learning assumes that students' overt behaviours and associated outputs can determine their level of cognitive engagement (Chi et al., 2018) and that this engagement produces distinguishable knowledge-change processes (Chi et al., 2018). The differentiated modes of activity can be mapped against levels of cognitive engagement; with Passive corresponding to minimal understanding, Active to shallow understanding, Constructive to deep understanding, and Interactive as deepest understanding (Chi & Wylie, 2014). In turn each level of cognitive engagement leads to specific knowledge-change processes (Chi & Wylie, 2014). So Interactive > Constructive > Active > Passive lead to the knowledge change processes of Co-Infer > Infer > Integrate > Store (Chi & Wylie, 2014). The authors argue that the primary hypothesis of ICAP has been validated through extensive laboratory and classroom research (Chi & Boucher, 2023). By mapping observable student behaviours during instructional activities to the underlying knowledge-change processes, teachers can gain insights into how students are engaging with the material (Chi, 2021). Furthermore, Chi (2021) argues that this approach provides a solution to the challenge of authentic learning environments like classrooms, where it's difficult for teachers to discern the specific knowledge-change processes occurring within students' minds.

The ICAP framework and learning analytics

Although Chi (2021) makes her case for the utility of the ICAP framework primarily within traditional classroom teaching, it is the contention of this paper that the ICAP framework is highly relevant and particularly well suited to online learning environments. Firstly, addressing the relevance, although educational computing was popularly thought to encourage active learning, research has revealed that it instead tends to support knowledge reproduction – a phenomenon associated with passive learning (Scardamalia & Bereiter, 1993). Additionally, it has been argued that active learning and student autonomy are of increased importance in online learning environments, which have reduced academic support and oversight (Wiseman et al., 2016). Furthermore, within online learning environments it is difficult for LDers and teaching staff to determine how learners are interacting with the online tools, and whether meaningful learning is occurring (Ruipérez-Valiente et al., 2015; Stepanek & Dorn, 2017). Wiseman et al. (2016) state that supporting and facilitating student engagement in online learning is the main challenge for educational technologists. While LA provides a method for gathering engagement metrics associated with online tools, ICAP may provide the framework for interpreting that data. Furthermore, ICAP, with its simplistic approach may help address the challenge of a generic predictive LA model that works optimally across multiple environments with diverse attributes, delivery styles, and assessment types (Broos et al., 2017).

The ICAP framework's focus on overt motoric behaviours (Chi & Wylie, 2014) additionally supports its suitability for online environments where student actions produce trace data which can be captured and measured using LA techniques. The ICAP framework has been applied to LA studies previously, including within video-based learning, where it was shown to be successful at identifying active learning behaviours within the trace data (Dodson et al., 2018; Stepanek & Dorn, 2017; Vale & Falloon, 2024). The Vale & Falloon (2024) study validated the results of their LA findings with a survey in which students were asked to self-report their learning behaviours and the motivations behind them; the results of which aligned with the behaviours and motivations as defined by ICAP. The authors contrasted their findings with other LA video-based learning studies that did not apply a theoretical framework (like ICAP) or a multi-method approach and suggested that these studies may have misinterpreted the results strengthening the case for a theoretically grounded approach (Vale & Falloon, 2024). Therefore, our study felt there was significant potential in adopting the ICAP framework for its LA intervention and that the research outcomes would contribute to a growing body of research around its application.

Model design and implementation

Data selection

The Canvas Learning Management System (LMS) through which the online MBA students access learning content and participate in activities provides multiple sources from which trace data may be extracted and analysed. Canvas has an analytics feature 'built in', however, the majority of these analytics relate to general admin or amount to page or content views, which offer limited insight into student behaviours. These page or content views may infer a student is oriented towards instruction, the minimum required action for the Passive mode (Chi, 2021), however the trace data on its own does not allow the LDer to infer any higher level of engagement. Furthermore, there is no student output from a page or content view through which the LDer can confirm the level of engagement. Our model for assessing student engagement in the online program made the deliberate decision to exclude this data from the evaluation and focus instead on a sub-set of tools that were developed around active learning principles and that produce observable student output.

An internally developed suite of interactive tools was developed to enhance the learning experience within the online MBA. These tools provide 'activity types' that facilitate interaction with learning material and with other users. The online MBA is designed according to active learning principles in which students are expected to apply the knowledge taught. These tools produce the primary activities (excluding summative assessments) through which this applied learning occurs. Therefore, engagement with these tools may infer student engagement with the subject knowledge of the course. The following are a non-exhaustive list of some of the activity types produced by the tools with a brief description of student action and possible teaching application:

- **Multiple-choice quiz with instant feedback:** Students answer questions and receive automatic feedback. These quizzes can be used for knowledge checks, simple recall, or exploratory and priming questions that provide further resources or direction in the feedback.
- **Drag-and-drop activity:** Students assign items to the correct or relevant category. These activities can be used for knowledge checks, simple recall, and understanding key concepts, terms, or processes.
- **Poll:** Students select from a series of pre-populated statements. These activities can be used to activate prior learning, assess students' understanding of key concepts or gauge student opinion.
- **Word cloud:** Students can build a word cloud through simple text input where the most frequent words are presented in larger fonts. This tool can be used as a priming activity to activate prior learning, gauge cohort mood, and understand aggregate levels of familiarity or knowledge of a topic at the start or end of a module.
- **Short answer question:** Students submit short answers, receive feedback and/or can view other students' answers after submission. Students can additionally respond to and discuss the answers provided by other students. This tool is useful for formative questioning on new topics, generating ideas across a cohort, and comparing learner responses to prompts.
- **Collaborative debate activity:** An asynchronous debate platform where students can discuss and debate contentious or complex concepts. This tool helps in developing critical reasoning, evidence gathering, and co-generating ideas.

The activity types can be mapped against the ICAP modes of engagement based on the output they are designed to produce. For example, an activity type like a 'Multiple-choice quiz', 'poll', or a 'drag and drop' result in some manipulating of instructional materials and therefore can be mapped against the Active mode of engagement. These activity types do not allow the generating of new content so cannot be considered within the Constructive mode. On the other hand, a 'Word cloud', a 'Poll' (provided it also includes a required response field), and a 'Short answer question activity', require the learner to generate new content and therefore can be mapped to the Constructive mode. Finally, the 'Debate activity' in which students make an initial post (in response to an instructor prompt or activity instructions) as well as respond to peers' posts creates the potential for co-generative knowledge construction and therefore sits within the Interactive mode. Additional Interactive activity types could include the 'Stick-it board' (a posting and commenting tool), and the 'Peer video exchange' (allows students to post videos and comment on/discuss peers' videos) among others. Student interaction with these activity types create trace data, such as 'view', 'click', 'submit', and 'action' ('action' is unique to the specific activity type), which can be captured and visualised through an LAD. Although these activity types can be mapped to the ICAP framework based on expected student engagement, analysis of the student output would be necessary to more precisely confirm the nature of the engagement (Chi, 2021). ICAP can provide the LDer with a simple heuristic to identify and differentiate between active learning tasks and select the one appropriate to maximise cognitive engagement (Chi & Boucher, 2023). This is not the only consideration when designing for student learning, however it does provide a practical application within a narrow focus. Furthermore, it is argued that the simplicity of the model vastly increases the contexts in which it may be applied (Chi, 2021). In Table 1, the activity types are mapped against and integrated into Chi and Boucher (2023)'s table to operationally define the ICAP modes (note this is a non-exhaustive list of example activity types).

Table 1:
ICAP Modes, their operational definition and corresponding activity types

Heuristic indices	Passive	Active	Constructive	Interactive
What physical behaviours are present?	Orienting or attending behaviours	Manipulating behaviours	Generating behaviours	Reciprocally cogenerating behaviours
What visible outputs (if any) are produced?	No visible outputs produced	Visible outputs contain information provided in the instructional materials	Visible outputs contain information that goes beyond the existing instructional materials	Visible outputs contain information that goes beyond 1) the instructional material and 2) a partner's contributions
	Corresponding activity types			
	N/A	• Flexible quiz • Poll • Drag & drop • Fill in the blanks	• Word cloud • Poll (with additional response field) • Short-answer question	• Stick-it board (allowing 'likes' and 'peer comments') • Debate activity • Short-answer question (with 'likes' and 'peer comments' enabled) • Peer video exchange and text chat
	Plausible cognitive or thinking processes			
	Storing new information	Activating, thereby strengthening relevant prior knowledge	Inferring new knowledge	Inferring new knowledge and building upon partner's knowledge

Note. Adapted from "Applying the ICAP framework to improve classroom learning," by Chi, M. T., & Boucher, N. S. (2023), In their own words: *What scholars want you to know about why and how to apply the science of learning in your academic setting. American Psychological Association*, 94-110. (https://teachpsych.org/ebooks/itow). Copyright 2023 Society for the Teaching of Psychology.

Embedding in pedagogical practice

Applying recommendations from the literature to embed the LA intervention in pedagogical practice we adopted 'The Learning Analytics for Learning Design Conceptual Framework' as described by Bakharia et al. (2016). The Bakharia et al., (2016) framework breaks the LA intervention down into a number of steps; Types of Analytics, Comparative Analysis, Learning and Teaching Context, and Intervention Support Tools (contingency). The framework is centred around a teacher who analyses the data, applies the context and performs the intervention. The Bakharia et al., (2016) framework does not explicitly stipulate where an educational theory would be incorporated, however it would be assumed that elements within the learning and teaching context (e.g. course structure, curriculum design, LD associated with content materials etc.) would be informed by educational theory. Our model advocates for making the educational theory explicit and applying it to each step of the process, it should drive decisions regarding which tools and which types of analytics are included in the design, consulted during the teacher (in our case a designing academic and learning designer) analysis phase before finally informing any contingency. We will describe the application of our LA model within the stages of the Bakharia et al., (2016) framework.

Types of analytics

The activity types provide engagement data associated with Temporal (content and tool access), Tool specific (quiz access and completion as well as discussion posts) as well as Cohort Dynamics (which students had or had not accessed what content or tools) as defined by Bakharia et al., (2016). As previously discussed, there are additional data points available to the study (from within the LMS) for example page views and content views, however, as this data is unable to tell us about active student learning behaviours it was excluded from the analysis. This pedagogically informed approach directly addresses the critique that much LA research is driven by the data that can be captured rather than specific pedagogical goals (Drugova et al., 2024; Jivet et al., 2018). By analysing the data associated with the activity types, we can identify patterns of active student behaviour throughout the online learning environment. It is additionally possible to view aggregate data at the MBA program level and/or across multiple semesters; although this functionality is not necessary to the goals of the initial intervention. The data is captured live through a software program and APIs and is fed into a data warehouse, from where it can be called into the LAD. A learning analytics dashboard (LAD) is a "*single display that aggregates multiple visualizations of different indicators about learner(s), learning process(es) and/or learning context(s)"* (Schwendimann et al., 2016, p. 37). The data analysis and LAD were produced using the Microsoft Power BI platform. Power BI, short for Power Business Intelligence, is a data visualisation platform primarily used for business insights. A Power BI Pro or Premium license is needed to create and publish data visualisations; however, these visualisations can then be shared with anyone within the organisation via the Power BI app or embedded in the organisational SharePoint.

Comparative analysis

A test of the comparative analytics was conducted, which revealed insights of pedagogical importance. At the course level, the activity types could be ranked by level of 'impressions' (aggregate engagement) with more granular analysis identifying the sub-type of engagement (e.g., view, click, submit, and action). This could be visualised in a table format and/or colour coded within a bar graph. Individual student engagement could also be identified, including which activity they engaged with including the sub-type of their engagement. Within the online MBA the course level datasets are relatively small (50-100 students). Small datasets are often viewed as a negative, leading to study limitations, low statistical validity and/or compromised generalisability (Nguyen & Karunaratne, 2024). However, Nguyen & Karunaratne (2024) found that when LA results are interpreted alongside LD and educational theory, educators can use these insights to enhance their courses and support learners. Within the Bakharia et al. (2016) study, surveyed teachers were unanimous in desiring the capability to view statistics on course, content, and tool access within the LMS, which they felt, would help them align course design and the timing of key activities with how students were actually engaging with the content.

Learning & teaching context

Application of the ICAP framework to an LA model can infer student learning (and depth of learning) within the online MBA based on engagement metrics with specific activity types. However, it is unable to assess the value of that learning within the context of the learning outcomes of that course. The designing academic and learning designer (DA and LDer) play a crucial role in contextualising the analysis of the student learning data (Bakharia et al., 2016). In order to provide information on pedagogical context the visualisations within our LAD not only provide a descriptor of the activity type (e.g. Wordcloud, Multiple choice quiz etc.) but also the specific name of the activity as it is applied within the context of the course. For example, a Debate activity would also have a unique name such as ‘Data-debate’ or ‘Brand-risks’ or anything else given to it by the DA and LDer. Activity location (within the course) is also included and easily recognisable in the visualisation, which allows the DA and LDer to view that activity in context as well as quickly move to the activity for further investigation. Understanding which activities are (more or less) popular (in terms of student engagement) as well as which students are more actively engaged gives the DA and LDer an idea of the type and level of learning occurring within the course and inform any subsequent intervention. The LAD visualisations are presented in Figure 1.

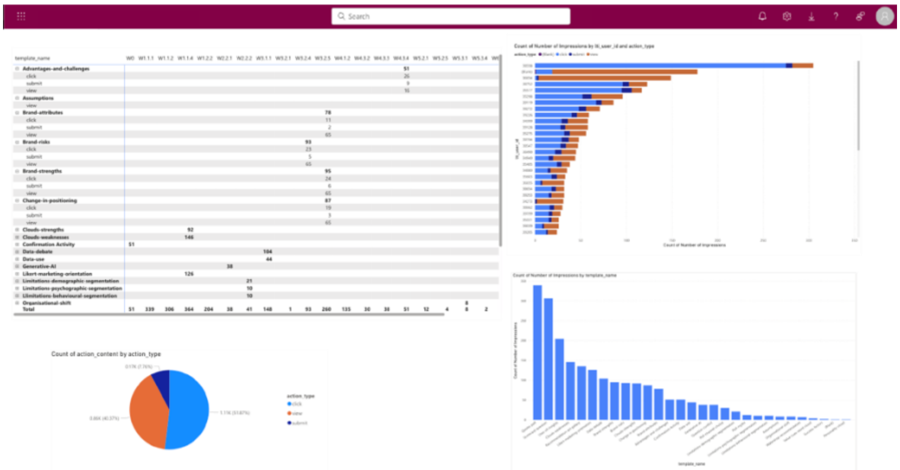

Figure 1. Comparative analysis of student engagement data associated with each activity type

Intervention support tools (contingency)

The ICAP framework contends that student learning as well as the depth of learning can be inferred from overt student behaviours (Chi & Wylie, 2014). By aligning the activity types with the corresponding ICAP modes, the DA and LDer can infer student learning based on engagement metrics with those tools (in consideration with learning and teaching context) while live tracking of engagement metrics allows for real-time feedback, enabling the DA and LDer to make prompt adjustments to course delivery. The insights provided by the dashboard may also inform the DA and LDer about optimal areas for resource investment to boost student engagement. Overall, this ongoing collection and analysis of data, support an iterative approach to course design and delivery, ensuring that learning environments are continually refined to meet learning and teaching needs.

Testing & future work

The next steps for the study involve integrating the model into the design and development practices of the DA and LDer within the online MBA program. This will require educator training in order for the DA and LDer to feel comfortable using the LAD and interpreting the results of the comparative data analyses. Once the model is integrated a number of studies will be conducted including longitudinal testing over multiple semesters, which will allow for an evaluation of impact on practice. Additionally, a longitudinal study will allow evaluation of the effect of the model on improvement of course design. These interventions might include design changes aimed at improving engagement metrics for activities identified as critical to the course's learning outcomes. This could potentially be measured in an increase (post-intervention) in the engagement metrics associated with activity types within the course as the ICAP framework infers that specific modes of activity denote specific levels of cognitive engagement. What would be more challenging but certainly worth investigating would be whether this higher level of engagement (specifically with higher order activity types) resulted in improved course learning outcomes. Alternatively, the DA and LDer may utilise the LAD to identify students with low engagement metrics and choose to contact them via email or discuss their engagement during 'face-to-face' sessions with academic staff. Appropriate ethics approval and student support are necessary prerequisites for either of these initial phase tests. We believe that the use of the ICAP framework and the model's targeted approach to LA make it a strong candidate for scalability and replicability. Therefore, engagement metrics can be analysed across multiple courses as well as at the program level, and over multiple semesters, significantly increasing the data available for analysis. This also enables multiple comparative analyses, which may lead to additional pattern recognition and insights. However, it is essential to acknowledge that such analyses may limit the context and LD expertise provided by the DA and LDer, which is a key feature of the Bakharia et al. (2016) model.

Conclusion

This paper has presented a conceptual evaluation model developed by Keypath Education and Melbourne Business School to analyse student engagement in a 100% online MBA program. Grounded in the ICAP theory for active learning, the study demonstrates how targeted LA interventions can visualise student engagement with online learning tools. Applying lessons from the literature the study identified and embedded the model in an established theory of learning and detailed the steps of model development against a recommended framework for embedding LA in LD practice. The paper further detailed how the inclusion of an explicit educational theory informed decision making at each of the steps within the framework. The paper proposes that the ICAP framework may be particularly well-suited for online environments and that by leveraging its insights, the proposed model may help bridge the gap between educational theory and practical application in online environments. Additionally, ICAP with its simple heuristic for identifying active learning, which is then used to infer cognitive engagement, provides a pathway for scalability and replicability missing from much LA work (Broos et al., 2017). The paper provides practical guidance for other universities looking to develop similar approaches to enhance understanding and support of their online student populations. By integrating established educational theories with advanced data analytics, the model not only addresses critiques within the LA field but also contributes to more effective and informed teaching practices in online learning environments. Future research will focus on validating and refining this model to ensure its broad applicability and effectiveness in various educational contexts.

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