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Navigating the Terrain:

Emerging Frontiers in Learning Spaces, Pedagogies, and Technologies

Do Beliefs About Intelligence Drive Engagement in Online Learning? Exploring the Impact of Growth and Fixed Mindsets

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This study investigates the relationship between students' beliefs about intelligence (fixed vs. growth mindset) and their engagement and behaviour in an online learning platform. The data was collected from 28 students enrolled in COMP90082 – Software Project subject at The University of Melbourne. Students' beliefs about intelligence were measured through a survey administered during the first week, while their online learning behaviours were captured through clickstream data from the learning management system. The study adopted a two-fold approach: first, students' learning strategies were identified through cluster analysis of their online session duration. By examining over 41,000 learning actions —such as accessing course materials, participating in discussions, and completing assignments— three distinct learning strategies emerged: "light", "light-intensive", and "intensive." Subsequently, the relationship between these learning strategies and students' beliefs about intelligence was examined using data visualisation techniques, chi-square tests, and logistic regression models. The findings revealed that students with a growth mindset were more likely to adopt intensive and engaged learning approaches within the online platform. Conversely, those with a fixed mindset tended to exhibit lower engagement levels and less intensive learning strategies. The study may contribute to the growing literature on the psychology of online learning and highlight the potential for tailoring instructional interventions and platform design to foster a growth mindset, thereby enhancing student engagement and academic success in digital learning environments.

Keywords: online learning behaviour, intelligence beliefs, learning management system, learning analytics, engagement

Introduction and Background

Despite the several benefits of online learning platforms, preserving student engagement and promoting participation remains a challenge. Several factors contribute to this challenge, such as personal traits which include self-regulation and motivation (Cho & Shen, 2013; Oliveira, 2013), and the layout and user experience of the online learning management system (LMS) itself (Maslov et al., 2021; de Barba et al., 2022; Oliveira et al., 2021). Beliefs about intelligence are encapsulated inside the idea of "mindsets". People preserve different beliefs about the character of intelligence, which may be labelled as a fixed or a growth mindset (Matthews, 2007). Those with a fixed mindset consider that intelligence is a static trait, while people with a growth mindset view intelligence as something that may be advanced via attempt and mastering. Students' beliefs about intelligence, especially whether or not they view intelligence as a set or malleable trait, can considerably impact their engagement and behaviour in learning environments (Matthews, 2007). Students with a growth mindset tend to demonstrate better engagement, persistence, and fulfilment in educational settings (Yeager &

Dweck, 2012). Interventions intended to foster a growth mindset can enhance educational fulfilment (Paunesku et al., 2015). Conversely, people who understand intelligence as a hard and fast trait frequently show decreased engagement and adaptability, especially while dealing with instructional challenges (Flanigan et al., 2017).

Student engagement is the interaction of the time, effort, and resources given by institutions and students, aiming to enhance learning experiences, outcomes, and institutional overall performance (Czerkawski & Lyman, 2016). Engagement is not just about participation but also involves emotional and cognitive dimensions (Peng, 2017). In online learning platforms, engagement can be influenced by various factors including (but not limited to): (i) effective instructional design that incorporates elements that facilitate interaction, practical engagement, and communication within the online environment (Czerkawski & Lyman, 2016; Borup et al., 2014), (ii) use of technologies that can enable easy access to subject materials (Peng, 2017), and (iii) teacher presence and effective engagement strategies including prompting student reflection, inquiry, and interaction (Czerkawski & Lyman, 2016; Peng, 2017).

Educational institutions have been consistently adopting LMS. LMS generate extensive trace data, capturing students' online learning actions such as webpage navigation and file downloads. This data provides an economical and objective measure of students' behaviours (or engagement) in online learning environments (Winne, 2020; Ye & Pennisi, 2022). Each record in the trace data typically includes the student's ID, the action's timestamp, and the corresponding URL, which indicates the content being accessed (Baker et al., 2020). Researchers categorise these actions based on their content and timing, grouping temporally close actions into sessions to better represent students' learning behaviours (de Barba et al., 2020; Tough, 1971). Learning actions can be categorised based on the content being visited, such as the subject's home page, lectures, or forums (Matcha et al., 2020). It can also be classified by the mode of learning considering the subject schedule, such as preparing ahead, revisiting, or catching up (Ahmad Uzir et al., 2020). Additionally, each learning action should not be analysed in isolation. Instead, actions that performed closely in time can be grouped into one learning session, defined as an uninterrupted sequence of learning activities (de Barba et al., 2020). This approach aims to more accurately represent students' online learning behaviours, as they often engage in related learning activities without interruption, creating a "psychological space" for focused learning.

Online learning sessions allow us to identify students' learning strategies. The learning strategy, or learning approach, was first introduced in the phenomenographic study by Marton and Säljö (1976). The term learning strategy describes and classifies how students engage in learning when they are in the learning environment with corresponding learning tasks. Research consistently identifies similar categories of learning strategies that students use when learning online, regardless of the specific learning contexts or techniques used. The intensive strategy involves critical evaluation and deep understanding of content, typically seen in students who are highly active and engage in a variety of learning activities (Jovanović et al., 2017; Matcha et al., 2020). In contrast, the light-intensive strategy (also referred to as strategic) is employed by goal-oriented students who focus their learning sessions on assessments (Maldonado-Mahauad, 2018). Finally, the light strategy (also called surface, selective, sampling, or disengaged) involves the acquisition of knowledge with minimal cognitive effort, often observed in students with low levels of online activity (Saqr et al., 2023).

In this context, this research aimed to discover how students' implicit theories of intelligence relate to their engagement and behaviour on online learning platforms. Specifically, we investigated how students' beliefs about intelligence (fixed vs. growth mindset) relate to their learning strategies in LMS. This study takes a novel approach by incorporating the temporal information on sessions into well-established learning analytics techniques for deriving learning strategies. By doing so, we can better understand how students with different beliefs on intelligence strategically distribute their time online over the semester across different subjects, offering deeper insights into their learning behaviours.

Method
Participants and Subject Setting

The study was conducted at The University of Melbourne in semester 1, 2023. Participants were recruited via e-mail and provided informed consent (Ethics approval #21436). The sample included a total of 28 (out of 171) students from the Master of Information and Technology program, undertaking COMP90082 – Software Project subject. Each teaching semester lasts 17 weeks, with 12 teaching weeks, one week of mid-semester break, one test revision week (SWOTVAC) and three exam revision weeks. The Software Project subject was taught in a mixed-learning setting with weekly in-person workshops and lectures that were delivered in-person and streamed online. Students had access to all the subject materials for these disciplines via the Canvas LMS.

Data Collection

We collected (i) clickstream data from Canvas LMS and (ii) participants' survey on their beliefs about intelligence (mindsets). The participants were surveyed at the start of the subject. Clickstream data was collected from Canvas LMS throughout the entire subject duration.

The LMS automatically records learners' behavioural data, such as their login history, time spent reviewing content, interactions in online discussions, and completion of activities. These digital trace data provide authentic and detailed information about students' actual learning behaviours in the online learning platform. The URL component permits researchers to categorise and assign a type to the learning action. For example, a URL containing "/assignments" might indicate that the student accessed the assignments, while a URL with "/files" could signify the student downloading a subject file. There were 41164 learning actions recorded in the Software Project subject during the semester for the 28 participants.

The survey was available to students during teaching week 1 of semester. The survey, adopted from (Lui et al., 2018), has six questions categorised into two categories - growth mindset ("No matter who you are, you can significantly change your intelligence level", "You can always greatly change how intelligent you are" and "No matter how much intelligence you have, you can always change it quite a bit") and fixed mindset ("You have a certain amount of intelligence, and you can't really do much about it", "Your intelligence is something about you that you can't change very much" and "You can learn new things, but you can't really change your basic intelligence"). Each question is answered using a 5-point Likert Scale; "1-Strongly Disagree", "2-Disagree", "3-Neither Disagree nor Agree", "4-Agree" and "5-Strongly Agree".

Data Analysis

Determining whether two successive online learning activities were part of the same session was a fundamental assumption in the definition of learning strategies. Since lectures and workshops in the Software Project subject lasted an hour, activities that happened within an hour of one another were combined into a single session. As a result, 2484 sessions were identified and analysed in the Software Project subject. The student learning sessions were categorised based on their duration. Sessions lasting less than 5 minutes were defined as small sessions, those ranging from 5 to 30 minutes were considered medium sessions and sessions exceeding 30 minutes in duration were classified as large sessions (de Barba et al., 2020).

To identify each student's learning strategy (i.e. the way they engage with online learning contents, as introduced earlier), a one-way clustering method was employed based on small (s), medium (m) and large (l) sessions. We tested two methods, K-Means clustering and agglomerative hierarchical. Agglomerative hierarchical clustering was implemented using various linkage methods, including Ward, single, complete, centroid, and average linkage. The optimal cluster number in K-Means was found using the Elbow plot and Silhouette score. In agglomerative hierarchical clustering, the optimal cluster number is found using a dendrogram (Song et al., 2024). The Silhouette score was 0.42, which indicates that the clusters identified by K-Means is not very well-defined. The different linkage methods were compared using the adjusted Rand index, and the Ward method was found to be the most suitable. The R "mclust" library was utilised for the implementation. Additionally, multiple scatter plots were used to illustrate the relationship between these learning strategies and the weekly mean hours spent on learning activities.

Data visualisation methods were employed to find patterns in the relationship between learning strategies and beliefs about intelligence. Histograms were used to show the weekly action levels, as temporal patterns highlight periods of heightened and lower engagement within the online learning environment. Multiple bar charts were employed to showcase the relationship between the answers to each survey question and the student's learning strategies. Since the survey contained two types of questions – fixed mindset and growth mindset, these six questions were combined into these two categories, and the overall relationship between learning strategies and beliefs about intelligence. Chi-square tests were conducted to determine if each survey question and learning strategy were independent. The survey questions represent one categorical variable, and the learning strategies represent the other categorical variables. Significantly related questions for both fixed and growth mindsets were identified, and logistic regression models were constructed. It is a suitable choice since the outcome variable (i.e., the learning strategy) is categorical, and the goal is to model the relationship between the outcome and one or more predictor variables (i.e., the survey responses). These analyses aimed to uncover the potential connections between students' beliefs about intelligence and their adopted learning strategies, which could inform tailored interventions or support mechanisms to foster more effective learning behaviours.

Results

Identifying Students' Learning Strategies and Mindset

Students had a high initial activity in Week 1, followed by fluctuating levels throughout the semester, with an overall declining trend from the initial peak until the end of the semester, as shown in Figure 1. Distinct peaks are observed during the mid-semester break (Week 07B), week 12 and exam week 1 (X1), highlighting activity potentially driven by assessment deadlines (i.e., Week 4, 8 and exam week 1). However, a high number of actions does not necessarily mean a high number of sessions or extended learning time. Therefore, Figure 2 shows plots with each student's interaction with the LMS considering their counts of actions (left), sessions (middle) and hours (right).

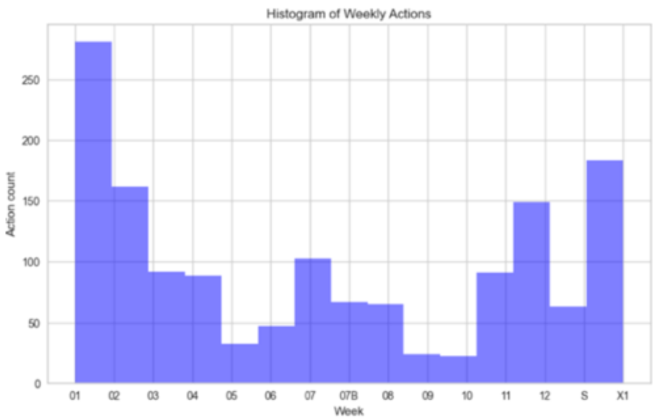

Figure 1. Count of actions based on weeks.

Each session was labelled small (s), medium (m), or large (l) as per Method section, and were used in the clustering analysis, accounting for the varying lengths and activity levels of learning sessions. The dendrogram analysis from the agglomerative hierarchical clustering revealed three clusters: cluster 1.0 – (n=22), cluster 2.0

(n=4), and cluster 3.0 (n=2). By investigating the properties of each cluster, we labelled each as an engagement strategy (or learning strategy), ranking from lower to higher engagement named "light" (Cluster 1.0), "light-intensive" (Cluster 2.0), and "intensive" (Cluster 3.0).

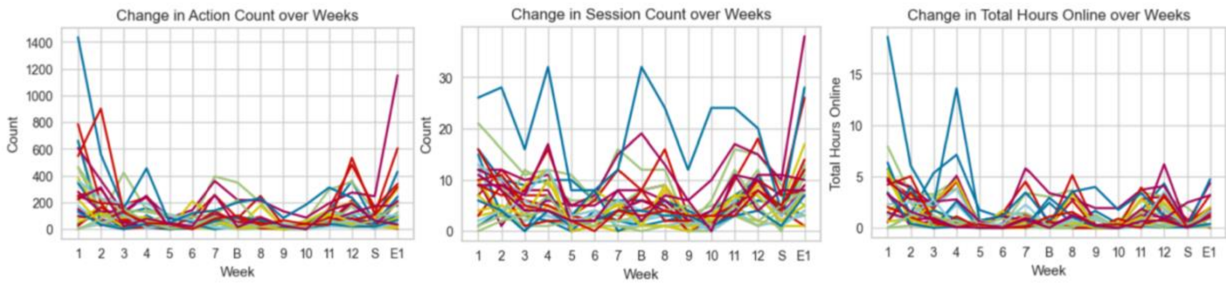

Figure 2. The weekly action counts (left), session counts (middle), and total hours online (right) for all 28 students.

Interpreting Patterns of Learning Strategies and Beliefs on Intelligence

Across the three learning strategy clusters agreed with fixed and growth mindset beliefs to varying degrees. (Figure 3). Students in the "intensive" learning strategy cluster all had a higher response for growth mindset beliefs, while the "light-intensive" and "light" strategy clusters also show a tendency towards higher or neutral growth mindset levels. The "intensive" learning strategy cluster had all students endorsing lower levels of fixed mindset beliefs, while the "light-intensive" strategy cluster had more equal distribution, and the "light" strategy cluster had many students agree with higher levels of fixed mindset beliefs.

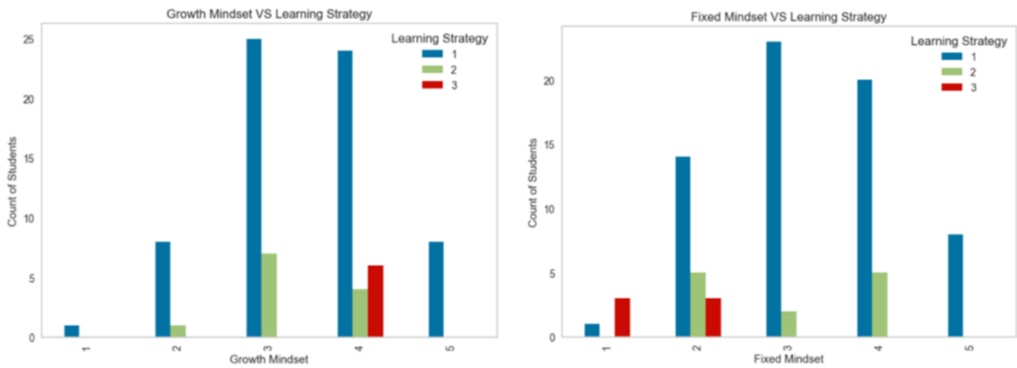

Figure 3. Count of students based on two types of beliefs of intelligence (Growth and Fixed mindset) with different learning strategies. Learning Strategy: light (1 Blue), light intensive (2 Green) and intensive (3 Red).

The analyses then moved to investigating each question individually, aiming to identify specific survey questions that would discriminate among the clusters. Figure 4 presents a series of scatter plots highlighting the relationship between each student's responses to survey questions per cluster and their weekly mean hours spent on learning activities. Students in the "light" cluster (1.0) tend to have lower weekly mean hours spent on learning activities, regardless of their growth mindset beliefs. In the growth mindset scatter plots, there seems to be a positive trend between stronger growth mindset beliefs (higher x-axis values) and increased weekly mean hours spent on learning activities for students in the "light intensive" cluster (2.0). However, in the fixed mindset scatter plots, the relationship is less clear, with no obvious pattern emerging. In both the growth mindset and fixed mindset scatter plots, students in the "intensive" cluster (3.0) tend to have higher weekly mean hours spent on learning activities, regardless of their mindset beliefs.

The chi-square test of independence was used in our analysis to evaluate whether the distribution of responses to each survey question was independent of or related to the learning strategies (Table 1). Two survey questions indicated a significant relationship between the question and the learning strategies. Logistic regression models were then used to identify the probability of belonging to each learning strategy based on the given mindset. To evaluate the performance of the logistic regression model, the clickstream dataset was split into a training set (70% of the data) and a testing set (30% of the data).

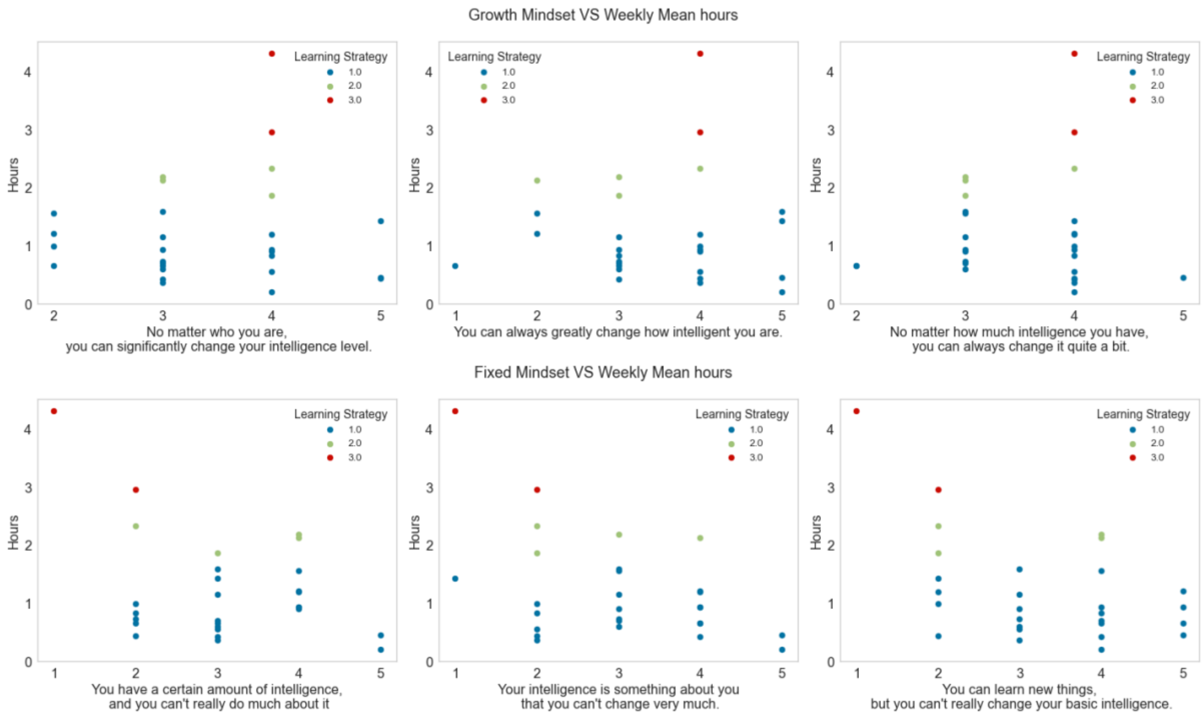

Figure 4. Two types of beliefs of intelligence (Growth and Fixed mindset) against weekly mean hours based on different learning strategy clusters. Learning Strategy: light (1 Blue), light intensive (2 Green) and intensive (3 Red). Intelligence Beliefs X-Axis: Likert Scale from 1-Strongly Disagree to 5-Strongly Agree.

To evaluate the performance of the logistic regression model, the clickstream dataset was split into a training set (70% of the data) and a testing set (30% of the data). This ratio is a widely accepted practice in machine learning and data science (Friedman, Hastie, & Tibshirani, 2001). The rationale behind this split is to provide enough data for the model to learn patterns and relationships (training set) while reserving a significant portion to assess its predictive accuracy on unseen data (testing set). By using 70% of the data for training, the model can develop a robust understanding of the dataset, and the 30% reserved for testing allows for a reliable evaluation of its generalization performance (Goodfellow, Bengio, & Courville, 2016). The model was trained on the training set and then evaluated on the unseen testing set. The provided results show an overall accuracy of 0.85, indicating that the model correctly predicted the learning strategy 85% of the time on the testing set.

Table 1
Chi-square test of independence between each survey question and learning strategies.

Mindset	Survey Question	p-value
Fixed	You have a certain amount of intelligence, and you can’t really do much about it	0.0379*
Growth	No matter who you are, you can significantly change your intelligence level	0.4450
Growth	You can always greatly change how intelligent you are	0.6611
Fixed	Your intelligence is something about you that you can’t change very much	0.3638
Fixed	You can learn new things, but you can’t really change your basic intelligence	0.0151*
Growth	No matter how much intelligence you have, you can always change it quite a bit	0.6160

Note. *indicates significant at the 0.05 level

Regarding the two statistically significant survey questions, the model achieved a precision of 0.78, recall of 1.00, and F1-score of 0.88 for the "light" cluster (Table 2). Conversely, the model struggled with the "light-intensive" strategy, with precision, recall, and F1-scores of 0.00. There is no test data for "intensive" since the dataset only consists of two "intensive" strategy students and both of the data are in the training dataset. The macro-averaged metrics provide an overall assessment of the model's performance, accounting for class imbalance. The macro-averaged precision of 0.39, recall of 0.50, and F1-score of 0.44. The coefficients for the survey questions that were significantly related to the learning strategies are presented in Table 3.

Table 2

The logistic regression evaluation for the survey questions "You have a certain amount of intelligence, and you can't really do much about it" and "You can learn new things, but you can't really change your basic intelligence".

Learning Strategies	Precision	Recall	F1-score
1.0 – light	0.78	1.00	0.88
2.0 – light intensive	0.00	0.00	0.00
3.0 - intensive	N/A	N/A	N/A
accuracy			0.78
macro average	0.39	0.50	0.44
weighted average	0.60	0.78	0.68

Table 3

Coefficients for each survey question that were significantly related to the learning strategies

Survey Question	Light strategy	Light-intensive strategy	Intensive strategy
You have a certain amount of intelligence, and you can't really do much about it	0.5935	0.3370	-0.9306
You can learn new things, but you can't really change your basic intelligence	0.7565	0.1438	-0.9004

Discussion

The findings of this study provide insightful observations into the relationship between students' beliefs about intelligence and their learning engagement in an online learning environment. Students who held a growth mindset tended to adopt more intensive and engaged learning approaches within the online platform. This relationship aligns with previous research demonstrating the positive impact of a growth mindset on academic achievement, persistence, and adaptive learning behaviours (Blackwell et al., 2007; Yeager & Dweck, 2012).

We found that students exhibiting a "light" learning strategy did not appear to have a strong relationship between their intelligence beliefs and their behaviours. This observation highlights the complexity of the relationship between students' beliefs of intelligence and learning engagement. We expect that other factors, such how students regulate their learning (e.g., effort regulation, de Barba et al., 2020), may also play a significant role in shaping the learning behaviours of students who are already disengaged or exhibiting low levels of activity within the online learning environment.

However, the chi-square tests identified two survey questions that were significantly related to students' learning strategy clusters: "You have a certain amount of intelligence, and you can't really do much about it" and "You can learn new things, but you can't really change your basic intelligence". The logistic regression model analysis, presented in Table 3, provides a quantitative framework for quantifying the association between responses to these fixed mindset questions and the probability of belonging to each learning strategy. For the first question, the positive coefficients for the "light" (0.5935) and "light-intensive" (0.3370) strategies align with the expectation that stronger agreement with a fixed mindset belief would be associated with lower engagement levels and less intensive learning approaches. Conversely, the negative coefficient for the "intensive" (-0.9306) strategy indicates that as students endorse a fixed mindset belief more strongly, they are less likely to adopt an intensive, highly engaged learning strategy. For the second question in Table 3, the positive coefficients for the "light" and "light-intensive" strategies (0.7565 and 0.1438, respectively) suggest that agreeing with this fixed mindset statement increases the likelihood of adopting these less intensive learning strategies. Conversely, the negative coefficient (-0.9004) for the "intensive" strategy implies that endorsing this fixed mindset belief decreases the probability of exhibiting an intensive, highly engaged learning approach.

Overall, the analysis reveals that students' beliefs about intelligence as a fixed or growth trait is related to their engagement behaviours in their online learning platform. In this study, we were able to particularly identify two survey questions measuring students' fixed mindset in their learning that were able to predict students learning strategies.

Implications for Educators

The findings of this study have practical implications for instructional designers, educators, and online platform developers. By understanding the link between beliefs of intelligence and different learning engagements, targeted interventions could be implemented to foster a growth mindset among students. These interventions could take various forms, such as mindset-oriented instructional materials, growth-mindset prompts or exercises, or personalised feedback and support mechanisms within the online learning platform (Paunesku et al., 2015). Additionally, the insights from this research could inform the design and user experience of online learning platforms, emphasising features and tools that promote active engagement, challenge-seeking, and persistence elements aligned with a growth mindset approach. Adaptive learning systems could leverage mindset data to provide personalised recommendations, resources, and support tailored to individual students' mindset profiles, potentially enhancing their engagement and academic performance. By actively cultivating a growth mindset and creating online learning environments that reinforce and support this mindset, educational institutions and platform providers can potentially enhance student engagement, academic achievement, and overall learning outcomes in the rapidly evolving landscape of online education.

Limitations and Future Work

While the logistic regression model provides valuable insights into the relationship between beliefs about intelligence and learning engagement, this study has several limitations. One limitation is the imbalanced nature of the students' online learning behaviours. Specifically, the clustering algorithm we used is widely adopted in existing research, but the result showcases a disproportionately larger number of students classified as having a "light" learning strategy compared to the "light-intensive" and "intensive" strategies. One possible interpretation is that most students wanted to pass our subject of interest with minimum effort. This class imbalance problem likely contributed to the logistic regression model's struggles in accurately predicting the minority classes, as evidenced in our results section. Additionally, the dataset represents a single course from the university, which may limit the generalisability of the findings to other educational contexts or student populations.

Future research could explore techniques such as oversampling, undersampling, or employing more advanced machine learning algorithms that can handle imbalanced datasets effectively. Longitudinal studies tracking students' intelligence beliefs and engagement patterns over multiple semesters or courses could provide a deeper understanding of how mindset beliefs and learning strategies evolve as students' progress through their academic journey. Additionally, incorporating factors such as self-regulation, motivation, and specific design elements of the online learning platform could lead to more holistic models and intervention strategies tailored to the unique needs and characteristics of individual students. By addressing these limitations and expanding the scope of research, educators and platform developers can better understand and support diverse student learning experiences in online environments.

Conclusion

The findings of this study provide valuable insights into the relationship between students' beliefs about intelligence and their engagement in online learning environments. Students with a growth mindset were more likely to adopt intensive and engaged learning strategies, while those with a fixed mindset tended to show lower engagement levels. These results suggest that fostering a growth mindset could enhance student engagement and academic success in online learning platforms. Future research should explore interventions to promote a growth mindset and investigate the impact of such interventions on student learning outcomes. Additionally, the design of online learning platforms should consider incorporating features that support the development of a growth mindset, thereby potentially improving the overall educational experience for students.

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