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Integrating Learning Analytics into the Flipped Classroom: A Study on Data-Enabled Flipped Learning

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Abstract

The study explores the integration of Learning Analytics with the Flipped Classroom approach to improve student learning outcomes. The resultant Data-Enabled Flipped Learning (DEFL) model seeks to tackle challenges students face in comprehending and assimilating knowledge in a Business Analytics course. Educators can adapt teaching methods to individual student needs by strategically using pre-class surveys, in-class interventions, and post-class feedback. The efficacy of the DEFL model is shown via a quasi-experimental design, which highlights significant enhancements in students' understanding of specific topics. Interestingly, students who initially assessed themselves lower showed notable improvement in performance. A comparison of cohort grades further reinforces the model's capacity to elevate overall course outcomes. While recognising its constraints and proposing future refinements, the research emphasises DEFL's potential to redefine contemporary education, providing educators with an effective instrument for tailored instruction and enhanced student achievements.

Subject Areas

Education Technology

Keywords

Flipped Classroom, Learning Analytics, Data-Enabled Flipped Learning

1. Introduction

The Flipped Classroom approach, designed to boost student retention and understanding, has significantly departed from traditional teaching methods. In this model, learners first acquire fundamental concepts independently through asynchronous pre-class videos created by teachers (Baytiyeh, 2017) [1]. This process allows students to interact with the content at their own pace, ensuring they come to class ready to apply their knowledge in active discussions with instructors and classmates (Milman, 2020) [2]. Within this setup, instructors transition from mere information conveyors to active facilitators, steering student conversations, sharing specialised insights, and leading hands-on sessions (Hwang *et al.*, 2019) [3]. However, while the flipped classroom offers numerous benefits, its adoption has obstacles. Teachers might struggle with labour-intensive content creation, technological barriers, and the need for students to adopt a more self-directed learning approach, which some might resist (Bishop & Verleger, 2013 [4]; Abeysekera & Dawson, 2015 [5]). Additionally, how consistently students engage with pre-class resources can greatly affect in-class activity success (Kim *et al.*, 2014) [6]. Given these challenges, recent scholarship suggests integrating Learning Analytics (LA) into the Flipped Classroom model. Utilising LA allows educators to track student involvement, assess performance, and furnish real-time feedback, refining the flipped classroom experience (Gašević *et al.*, 2015) [7]. With the capabilities of LA, combining these two educational strategies appears to be a potent means to elevate student outcomes, providing educators with a deeper understanding of student interactions and enabling swift course adjustments (Siemens & Baker, 2012) [8]. The Data-Enabled Flipped Learning (DEFL) model is at the heart of this combination. This model merges the Flipped Classroom approach with insights from Learning Analytics. The DEFL model is based on a three-pronged approach:

1) Pre-Class Surveys: Before in-person sessions, students complete surveys evaluating their grasp of asynchronous video content. These surveys collect information on student confidence, uncertainties, and remaining questions. With Learning Analytics, educators can interpret these answers, gaining a broad view of classroom readiness and pinpointing subjects needing more focus.

2) In-Class Interventions: Based on the pre-class survey results, teachers can modify in-class exercises to address student requirements better. If a topic proves challenging for many, more time can be allocated to elucidate it. Moreover, real-time LA can be utilised during classes to gauge and refine teaching approaches based on instant feedback.

3) Post-Class Feedback: After sessions, students share feedback on their understanding, clarity of topics covered, and suggestions for enhancement. Analysing this data through LA provides educators insights into effective pedagogical methods and topics that may benefit from additional review in subsequent lessons.

Thus, embedding LA into the flipped classroom method is viewed as a potential path to enhance student outcomes, offering a window into student behaviours and an avenue for timely course modifications (Siemens & Baker, 2012) [8]. This study assesses the effectiveness of integrating LA with the Flipped Classroom approach within the DEFL framework for the Business Analytics course at the Singapore Polytechnic School of Business. The primary research questions are:

1) How does the DEFL model, blending the Flipped Classroom approach with Learning Analytics, affect student understanding and knowledge absorption?

2) How much does the DEFL approach improve student outcomes compared to traditional teaching methods?

Given these research queries, we must position our study within the broader academic context. The subsequent literature review section delves into previous research and foundational theories surrounding Flipped Classrooms and Learning Analytics. The goal is to highlight this study's unique contributions while identifying under-researched areas.

2. Literature Review

2.1. Prospects and Challenges of Flipped Classroom

The efficacy of the Flipped Classroom approach has been critically evaluated, reflecting insights from both educators and students. Adopting a Flipped Classroom methodology has been linked with a myriad of advantages. It is believed to facilitate active learning (Alhasani, 2015) [9] and foster critical thinking both within the classroom setting and beyond (Herreid & Schiller, 2013) [10]. Moreover, it enhances student engagement, fosters frequent feedback exchanges between students and educators, and allows for a self-paced learning environment (Goodwin & Miller, 2013 [11]; Horn, 2013 [12]; Mok, 2014 [13]). In an extensive review, Bishop and Verleger (2013) [4] scrutinised 24 studies centred on the Flipped Classroom model. Their analysis categorised these studies based on various criteria, including in-class and out-of-class activities, evaluation measures, and inherent methodological attributes. Their findings revealed ambivalent student perceptions of the Flipped Classroom approach. Certain students reportedly encountered challenges grasping concepts from online lectures, indicating a need for prompt interventions to enhance comprehension. This observation was echoed in other studies, suggesting that some students may struggle with directing their learning, leading them to attend classes without adequate preparation for active participation (Arnold-Garza, 2014 [14]; Herreid & Schiller, 2013 [10]).

2.2. Synergizing Flipped Classrooms and Learning Analytics

In scholarly discourse, Learning Analytics is a specialised field concentrating on the "measurement, collection, analysis, and reporting of data about learners and their contexts." Its primary ambition is to understand and enhance the learning experiences and the environments that enable them (Long & Siemens, 2011) [15]. **Figure 1** offers a detailed visualisation of the comprehensive steps involved in the Learning Analytics process.

Learning Analytics' core purpose is to equip educators with sophisticated methods to capture and interpret complex data from interactions between educators, students, and digital mediums (Mayer *et al.*, 2009) [16]. This approach is driven

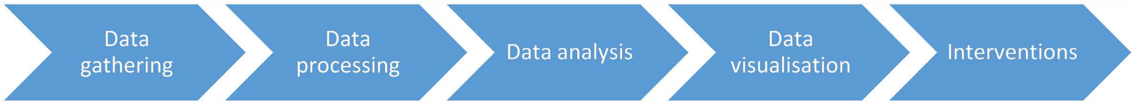


Figure 1. Learning analytics process.

by the desire to uplift the quality of educational experiences, allowing educators to refine and individualise their course structures with increased precision (Johnson *et al.*, 2014) [17]. While Learning Analytics is an emergent domain, its anticipated influence on reshaping pedagogical methodologies, especially when integrated with frameworks such as the Flipped Classroom, holds significant promise. Leveraging the data insights from Learning Analytics gives educators a detailed perspective on student learning patterns. This invaluable information can subsequently inform tailored pedagogical interventions, magnifying instructional effectiveness (Kovanovic *et al.*, 2021) [18] [19]. Integrating the Flipped Classroom paradigm with Learning Analytics heralds the onset of truly adaptive educational experiences. This integrative approach cultivates an environment wherein students are emboldened to engage in self-regulated learning, sharpening their metacognitive faculties through contemplative self-assessment (Jovanović, Gašević *et al.*, 2017) [20]. For educators, this amalgamation manifests as a vibrant feedback loop, fluidly bridging online and traditional classroom realms. With such cyclic feedback, educators can gauge and cater to student development, comprehension levels, and evolving learning requisites, solidifying a more comprehensive and adaptive teaching strategy (Klemke *et al.*, 2018) [21] [22].

Shedding light on the connection between Learning Analytics and the Flipped Classroom, Fernández *et al.* (2018) [23] [24] observed that earlier investigations into the Flipped Classroom did not adequately address how the infusion of Learning Analytics might bolster the educational activities within this pedagogical model. Similarly, Algayres and Triantafyllou (2020) [25] championed the broader incorporation of Learning Analytics into the Flipped Classroom, noting the extant limitations of current Learning Management Systems in effectively integrating Learning Analytics into Flipped Classroom scenarios. They contended that the synthesis of Learning Analytics and the Flipped Classroom unlocks opportunities for educators, offering refined insights into student learning processes, enhancing feedback mechanisms, and providing data-driven reflections for pedagogical advancements. This fusion, therefore, unveils a rich research frontier focusing on the augmentation of student learning experiences through the converging perspectives of both Learning Analytics and the Flipped Classroom. Notably, while Learning Analytics and the Flipped Classroom are individually vibrant research areas, explorations concerning their combined impact remain nascent.

2.3. The Data-Enabled Flipped Approach

To address the existing research gaps, the present study introduces a merger of Flipped Classroom pedagogy and Learning Analytics, culminating in a novel approach termed Data-enabled Flipped Learning (DEFL). This method harnesses the collective strengths of both pedagogies. Singapore Polytechnic has been pioneering various learning methods since 2021, and through these explorations, the institution has identified the paramount importance of gathering pertinent student learning data. The DEFL framework, as illustrated in Figure 2, unfolds across three pivotal phases: pre-class preparation, in-class interaction, and post-class feedback.

This model integrates asynchronous lecture sessions with active in-class participation, drawing from the Flipped Classroom methodology. Simultaneously, it employs Learning Analytics to gather student performance and interaction data within the Brightspace Learning Management System. Data about student engagement and comprehension is collated through quizzes embedded within asynchronous lectures, shedding light on individual and collective learning trajectories. In addition, the institution conducts weekly surveys to gauge students' grasp of the concepts discussed. The survey findings are meticulously analysed and then employed to tailor learning experiences during in-person tutorials, adapting based on the data amassed. After the culmination of each lesson, students undergo a quiz assessment to measure the success of the instructional interventions and to pinpoint those students who might benefit from supplementary support. By melding Learning Analytics with the Flipped Classroom approach, educators are better equipped to craft individualised learning experiences and gather pivotal data to drive informed pedagogical choices. Overall, the DEFL approach presents an all-encompassing and synergistic strategy to bolster student learning, promising to elevate educational outcomes for a diverse student body.

3. Methods

This study adopted a quasi-experimental research design to evaluate the efficacy

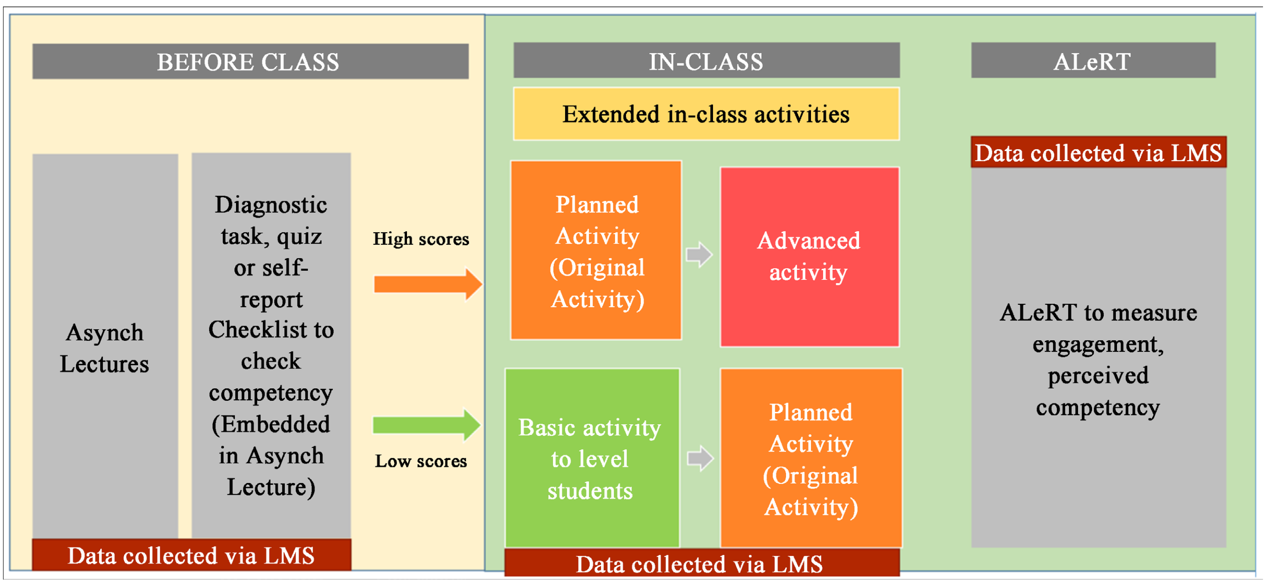


Figure 2. Data enabled flipped learning (DEFL) model.

of the DEFL model in enhancing students' comprehension levels. The design compared the pre-and post-test results from the DEFL intervention concerning students' understanding and knowledge within the BA2107 Business Analytics module. This module is offered to Year 2 students pursuing their Diploma in Business Administration (DBA) at the School of Business. The study's participants were sourced from nine Year 2 DBA classes, each containing approximately 20 students, culminating in 183 participants. Furthermore, four lecturers participated in implementing the DEFL model for this research. To minimise potential biases from teachers' prior experiences, all lecturers engaged in this research were introduced to the DEFL model for the first time.

The Business Analytics module incorporates lecturer-designed asynchronous lectures, tutorials, and hands-on lab sessions. These asynchronous lectures, aimed at imparting knowledge and concepts in business analytics, are hosted on the Brightspace LMS. Throughout the semester, students are tasked with viewing these lecture videos and completing weekly online quizzes. Furthermore, this module acquaints students with the functionalities and components of decision-making tools like Microsoft Excel and Tableau. The DEFL model was strategically integrated at three distinct intervals during the semester. Historical performance data from this module indicated that students frequently encountered challenges with Excel functions, dashboard creation, and data visualisation concepts. Therefore, to address these learning challenges, the DEFL model was activated during weeks 2, 4, and 13—corresponding to the periods these specific concepts were introduced. For instance, in the second week, students delved into advanced Excel functionalities, exploring functions such as "Match", "Offset", and "VLOOKUP" (refer to **Figure 3**).

After engaging with asynchronous lectures at each designated touch point, students complete a pre-tutorial survey (pre-test) to gauge their understanding of individual sub-topics in the online videos. This feedback is collected using a Likert scale, as depicted in **Figure 4**. Students who score two or lower on this scale are flagged for specialised assistance during the in-person tutorial. During these sessions, lecturers group students and tailor learning experiences based on identified needs. For instance, students who indicate challenges with topics such as "VLOOKUP" or "Picking list" receive extra exercises focused on these areas, enhancing their grasp of previously challenging subjects. Upon concluding the tutorial, students fill out a post-tutorial survey to assess any advancements in their understanding across the knowledge domains. This instructional approach, including its intervention methods, was consistently applied in Weeks 4 and 13. However, the survey questions varied to align with the topics covered during those weeks.

4. Analysis and Results

The research indicated that students faced challenges with specific topics within the module. **Figure 5** presents a portion of the student's pre-test results for

Module / Week	Lesson Topic	Lesson Outcome(s)	Intended Impact of ALeRT
BA2107 BA / Week 2	Using Excel Functions	• Business Analytics using Advanced Excel functions • Manage to locate data records using Match, Offset and VLOOKUP functions.	• Check students' prior understanding of the various Excel functions prior and post tutorial through Likert scale. • Check if the Likert scale has any improvement • Identify students who require targeted help on specific Excel functions

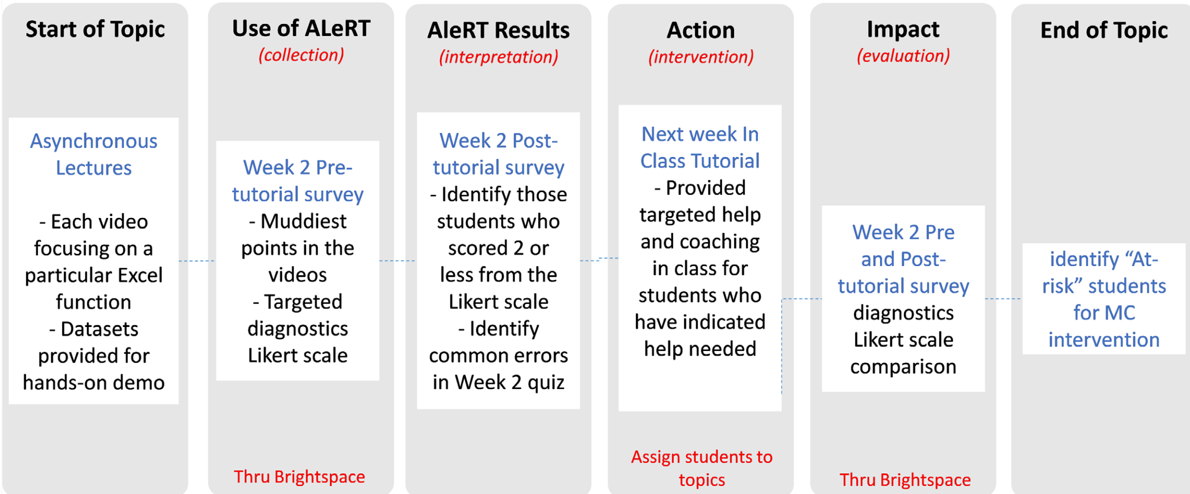
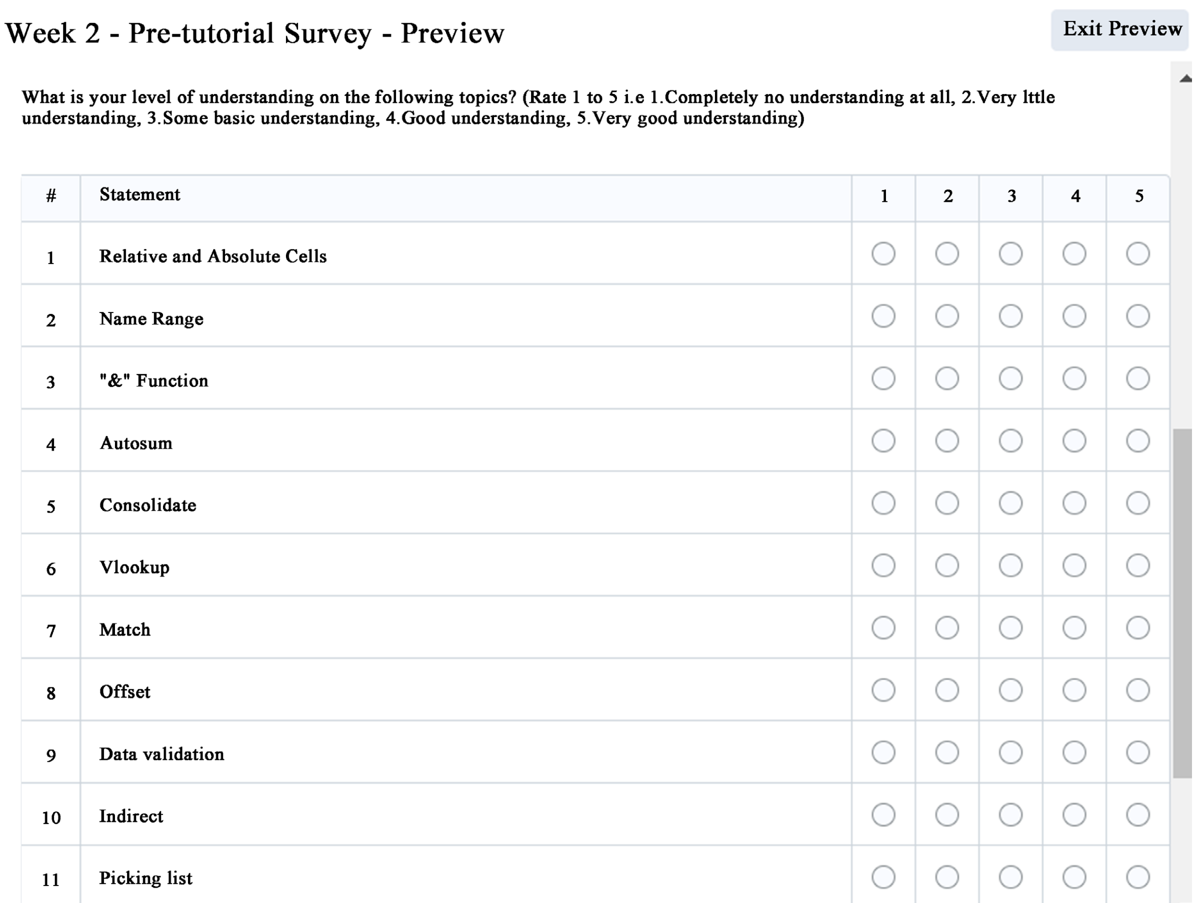


Figure 3. DEFL learning design plan for week 2 of BA2107 business analytics module.



Week 2 - Pre-tutorial Survey - Preview

Exit Preview

What is your level of understanding on the following topics? (Rate 1 to 5 i.e 1.Completely no understanding at all, 2.Very lttle understanding, 3.Some basic understanding, 4.Good understanding, 5.Very good understanding)

#	Statement	1	2	3	4	5
1	Relative and Absolute Cells					
2	Name Range					
3	"&" Function					
4	Autosum					
5	Consolidate					
6	Vlookup					
7	Match					
8	Offset					
9	Data validation					
10	Indirect					
11	Picking list					

Figure 4. Week 2 pre-tutorial survey.

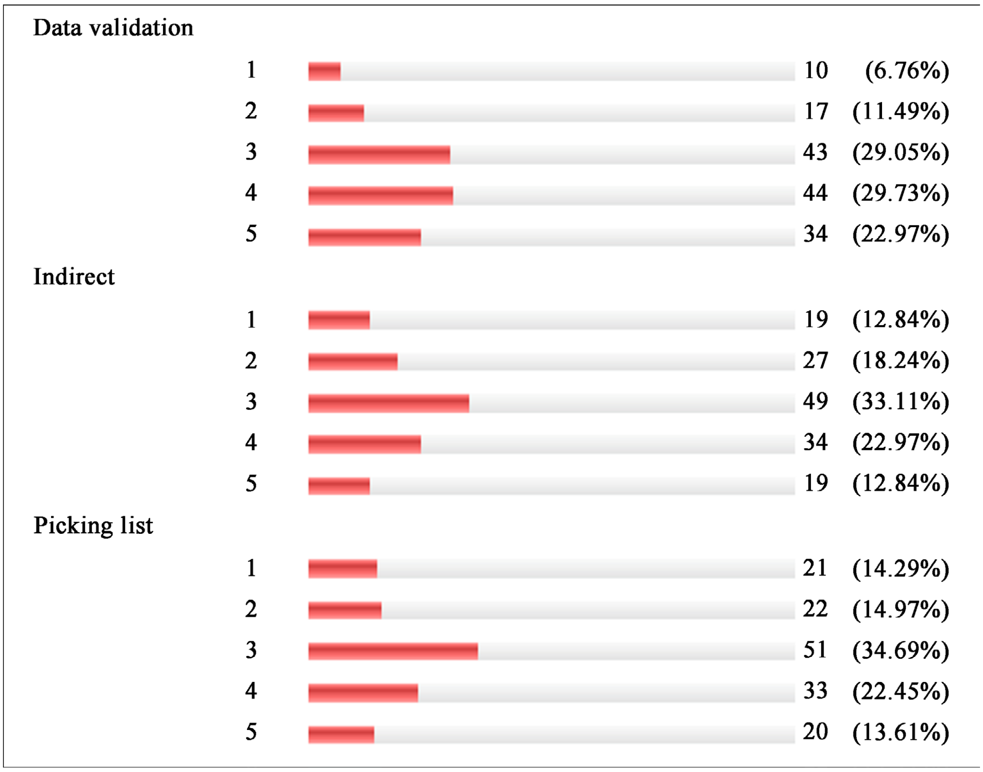


Figure 5. Students' pre-test results for week 2.

Week 2. An analysis of these results revealed particular difficulty in areas such as "Indirect", "Data Validation", and "Picking List". Students provided direct feedback, with comments including:

- "I find it challenging to use 'offset' and 'match' together."
- "I'm often uncertain about the appropriate functions to apply to certain questions."
- "What exactly is the role of the 'offset' and 'match' function?"
- "For 'If-Match type 0', there's no need for values to be in a specific order. So, why opt for 'match type 1' or '–1' when 'match type 0' seems universally applicable?"

In Week 4, as illustrated in Figure 6, students displayed difficulty with topics such as "Index (Indirect)" and "Dynamic commentary". Many found these concepts more challenging than foundational Excel functions. Direct feedback from students included:

- "The multitude of formulas can be overwhelming when creating the dashboard."
- "These concepts are more difficult to grasp than basic Excel functions."
- "If I don't use 'indirect' when creating 'Logo1', won't it just return the content of cell E3?"
- "I find 'indirect' puzzling."

In Week 13, as depicted in Figure 7, students encountered challenges with topics such as "Data Joins", "Pivoting", and "Sorting".

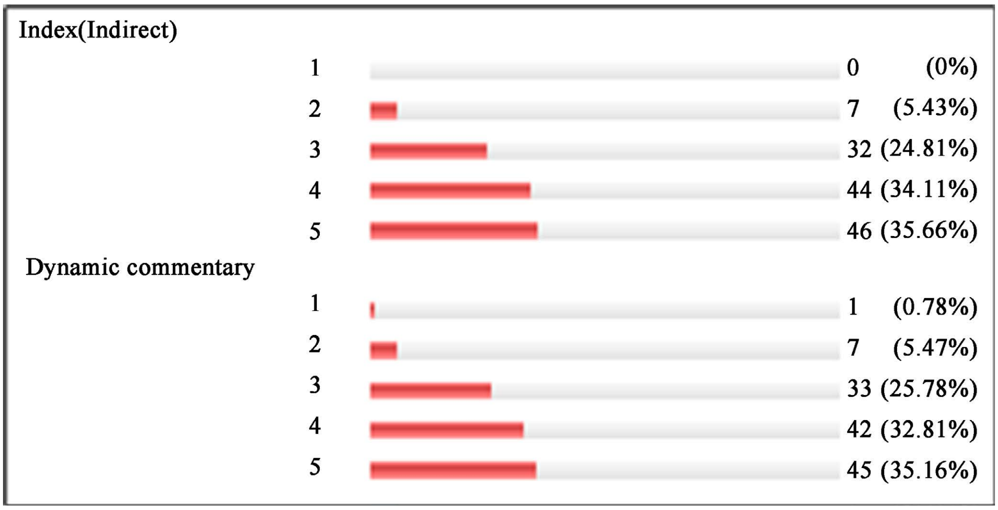


Figure 6. Students' pre-test results for week 4.

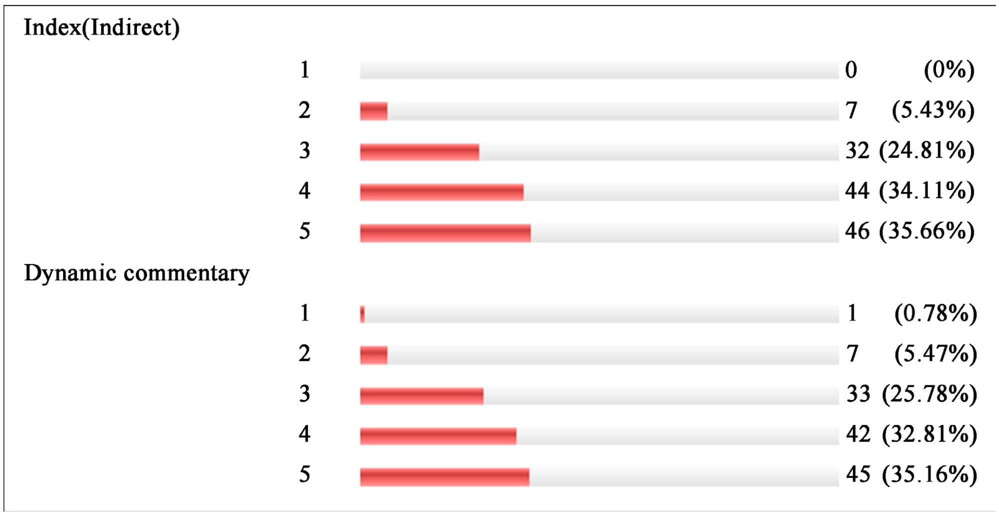


Figure 7. Students' pre-test results for week 13.

The results from the pre and post-tests for Weeks 2, 4, and 13 were aggregated and are presented in Figure 8. To ensure data privacy, individual student names were excluded. Instead, the average score for each topic was calculated per student for each touch point.

A one-way ANOVA was conducted based on the aggregated results. Figures 9-11 illustrate the outcomes of the ANOVA analysis, comparing the students' understanding levels for Weeks 2, 4, and 13. With a p-value less than the designated alpha value of 0.05, there was a statistically significant difference between the averages of the pre-test and post-test groups. This implies that the DEFL model intervention notably enhanced students' comprehension of the course content during Weeks 2, 4, and 13.

In addition to analysing the overall pre-post-test results for the entire cohort, the study examined whether students who initially rated themselves with a score of 2 or lower on the pre-test exhibited improvement in their subsequent

	W2 Pre-Test	W2 Post-Test		W4 Pre-Test	W4 Post-Test		W13 Pre-Test	W13 Post-Test
Wk2	3	5	Wk4	1	5	Wk13	1	5
Wk2	2	4	Wk4	1	3	Wk13	2	4
Wk2	1	5	Wk4	3	3	Wk13	2	5
Wk2	3	3	Wk4	2	3	Wk13	1	4
Wk2	1	3	Wk4	1	4	Wk13	2	3
Wk2	1	5	Wk4	2	5	Wk13	3	4
Wk2	1	5	Wk4	2	4	Wk13	2	3
Wk2	3	3	Wk4	3	3	Wk13	3	4
Wk2	3	4	Wk4	1	5	Wk13	1	5
Wk2	2	3	Wk4	1	3	Wk13	2	3
Wk2	3	4	Wk4	3	3	Wk13	1	3
Wk2	2	3	Wk4	1	5	Wk13	2	4
Wk2	1	5	Wk4	1	5	Wk13	2	4
Wk2	2	3	Wk4	2	5	Wk13	3	4
Wk2	2	5	Wk4	2	5	Wk13	3	3
Wk2	3	5	Wk4	3	3	Wk13	2	4
Wk2	3	4	Wk4	3	5	Wk13	2	4
Wk2	3	3	Wk4	1	5	Wk13	1	3
Wk2	1	3	Wk4	3	5	Wk13	3	3

Figure 8. Consolidated results of pre-post test.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
W2 Pre-Test	179	360	2.011173184	0.685267717
W2 Post-Test	179	723	4.039106145	0.667001444

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	368.0698	1	368.0698324	544.3736248	1.01212E-73	3.867712
Within Groups	240.7039	356	0.67613458			
Total	608.7737	357				

Figure 9. Differences between students' pre-post test results for week 2.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
W4 Pre-Test	177	345	1.949152542	0.684899846
W4 Post-Test	177	700	3.95480226	0.657036466

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	356.0028	1	356.0028249	530.5808057	2.99759E-72	3.868012
Within Groups	236.1808	352	0.670968156			
Total	592.1836	353				

Figure 10. Differences between students' pre-post test results for week 4.

post-test scores. Table 1 presents the distribution of these students, with the final column indicating their post-test outcomes. Using the data from Table 1, a one-tailed t-test was conducted. The results highlighted that the DEFL model intervention notably decreased the count of students assigning themselves a score of 2 or lower.

To further assess the DEFL model's impact on student's learning, the study employed ANOVA to contrast the mean grades of DBA students in the Business Analytics module with those from an earlier cohort. The final grades from the Academic Year 2021/22 (AY2122) were juxtaposed against those from 2022/23 (AY2223). Notably, the AY2122 DBA cohort did not experience the DEFL model intervention, while the AY2223 DBA students did. Figure 12 reveals that the average grades for AY2223 surpassed those of AY2122. This underscores the DEFL model's potential to bolster students' comprehension and overall course performance.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
W13 Pre-Test	179	339	1.893854749	0.612265395
W13 Post-Test	179	714	3.988826816	0.685267717

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	392.8073	1	392.8072626	605.4678051	8.34327E-79	3.867712
Within Groups	230.9609	356	0.648766556			
Total	623.7682	357				

Figure 11. Differences between students' pre-post test results for week 13.

Table 1. Pre-Post test results of students who rated themselves two or lower for the pre-test.

		Pre-Test	Post-Test
Week 2	Indirect	31.08%	2.61%
	Picking List	29.26%	3.51%
	Data Validation	18.25%	2.58%
Week 4	Index (Indirect)	5.43%	1.06%
	Dynamic Commentary	6.25%	1.05%
Week 13	Data Joins	6.02%	1.53%
	Pivoting	4.88%	1.54%

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
AY2122 Sem 2	204	14650.1	71.81422	73.63236
AY2223 Sem 2	183	13494.1	73.73825	70.04259

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	357.1055	1	357.1055	4.964254	0.026453547	3.865725
Within Groups	27695.12	385	71.93538			
Total	28052.23	386				

Figure 12. Comparison of students' grades AY2122 Sem2 vs. AY2223 Sem2.

From the provided data and research findings, several key points can be highlighted:

Statistical Significance

The one-way ANOVA between the pre-test and post-test results for Weeks 2, 4, and 13 indicates a statistically significant improvement in students' comprehension following the DEFL model intervention. This is evident by p-values less than the alpha value of 0.05. For students who rated themselves with a score of 2 or lower on the pre-test, the DEFL intervention resulted in a notable decrease in the number of students retaining this low rating in the post-test. For instance, the proportion of students struggling with the topic 'Indirect' plummeted from 31.08% pre-test to 2.61% post-test in Week 2. A comparison of final grades between the AY2122 and AY2223 cohorts showcases a positive difference. The AY2223 group, which experienced the DEFL model, performed better than the previous year's cohort, implying that the DEFL model's intervention significantly affected overall performance.

Practical Implications

Beyond statistical significance, the results indicate the DEFL model's genuine capacity to address specific challenges students face in the Business Analytics module, such as difficulties with "Indirect", "Data Validation", and "Picking List". The DEFL model aids students in navigating complex Excel functionalities, translating to better real-world applications, and increasing confidence in handling advanced analytical tools and topics.

Qualitative Feedback

Students' feedback provides a qualitative dimension to the results. The comments show that while students found certain functionalities and topics challenging, they consistently sought clarity and understanding. For example, queries about the role of functions like "offset" and "match" and the nuances between different "match" types suggest that students are engaged and eager to understand the intricacies of the content. Integrating Learning Analytics in their learning process was perceived positively overall. The feedback offers insights into students' struggles and allows the curriculum or teaching methodology to be tailored to address those areas of concern. For instance, seeing the challenges with "indirect" or "data joins" provides educators with clear action points for intervention and support.

5. Discussions

This research integrates Learning Analytics principles within a Flipped Classroom setting, culminating in the creating of the Data-Enabled Flipped Learning (DEFL) model. The DEFL framework delves into the analysis and interpretation of data relating to learner profiles, learning contexts, behaviours, and interactions, as proposed by Hwang and colleagues in 2017 [26] [27]. A primary aim of DEFL is to pinpoint students at risk and extend timely support, a sentiment echoed by Sclater and the team in 2016 [28]. The early identification of struggling students and prompt initiation of remedial action is vital, as noted by Alamuddin and others in 2016 [29] [30] and Wolff and colleagues in 2014 [31]. Tailored interventions by educators can alter student learning trajectories, steering them towards enhanced outcomes, as highlighted by both Lin-Siegler *et al.*, 2016 [32] and Fuchs *et al.*, 2016 [33] [34]. Empirical evidence underscores the DEFL model's efficacy in identifying learners needing early intervention. This research accentuates that the amalgamation of Learning Analytics and Flipped Classroom methodologies paves the way for informed tutorials via the DEFL framework. The success of this model holds promise for refining pedagogical practices at Singapore Polytechnic by equipping educators to craft a Flipped Classroom environment underpinned by DEFL principles. The advantages of the DEFL model extend to both educators and learners. Students, for instance, stand to gain enriched learning experiences and superior outcomes, as suggested by Lan and colleagues in 2014 [35] [36]. They can gain a nuanced understanding of their academic trajectory compared to their peers and obtain tailored resources, including personalised learning paths and feedback, as defined by Liu and the team in 2017 [37]. Educators, on the other hand, can closely monitor students' learning journeys, discern knowledge gaps, and orchestrate suitable interventions, as indicated by Xing and Du in 2019 [38]. Additionally, educators can refine their instructional designs to elevate their efficacy, as pointed out by Shivanagowda and associates in 2017 [39]. Within the confines of this research, the DEFL model has showcased its potential to amplify student learning outcomes.

6. Limitations & Future Research

The DEFL model, while promising, comes with limitations that must be acknowledged to gauge its applicability accurately. One significant limitation is the sample size used in the research. Suppose the study was conducted with a restricted number of participants or solely within an institution like Singapore Polytechnic. In that case, its findings might not entirely represent the broader educational community. As a result, any generalisations made beyond the studied sample could be potentially misleading. Another concern is the specificity of course content. It is plausible that the DEFL model was tested on distinct courses or content. This presents a limitation since some subjects might be inherently more receptive to the flipped classroom approach, while others might not derive the same advantages. Therefore, the DEFL model's efficiency might vary based on the course content it is applied to. Looking ahead, there are several areas ripe for future research and enhancements. The DEFL model could benefit from testing across a broader spectrum, spanning multiple institutions, diverse cultures, and a range of courses. This would provide a holistic view of its effectiveness across different educational landscapes. A salient theme emerging from the model's limitations is the crucial role of educator skillsets. Educators need adequate training for the DEFL model to reach its full potential. This calls for an investment in dedicated training programs, ensuring the model's widespread adoption and consistent implementation. Another area of improvement is in the realm of data analytics. Instead of expecting educators to comb through data manually, integrating advanced analytical tools could simplify this process. By automating parts of the analysis, educators can obtain insights more easily, ensuring a consistent interpretation of data. Incorporating a feedback mechanism where students can share their perspectives on the DEFL model would also be beneficial. After all, they are the end beneficiaries, and their insights can provide invaluable pointers for refinement. A long-term view is equally essential. While the immediate effects of the DEFL model are noteworthy, understanding its prolonged impacts on students' learning trajectories is paramount. This involves assessing their knowledge retention, adaptability in subsequent courses, and the practical application of the concepts they have learned. Furthermore, exploring how the DEFL model integrates or complements other established learning models could widen its applicability. Lastly, there is a clear need to streamline data collection and processing. By simplifying this phase, we can lessen the burden on educators and make the model more accessible. Integrating AI tools or improving the user interface for data analysis could be significant steps in this direction. The DEFL model heralds a new era in education. However, by acknowledging its limitations and continuously seeking improvement, we ensure it evolves in tandem with the ever-changing realm of modern education.

7. Conclusions

This study sheds light on the synthesis of Learning Analytics with the Flipped Classroom framework, culminating in the inception of the Data-Enabled Flipped Learning (DEFL) model. This study delved into gauging the prowess of the DEFL model in fortifying students' grasp and knowledge retention within a Business Analytics module. Rigorous data acquisition and interpretation revealed the pronounced positive effects of the DEFL model on students' academic results. Our findings illuminate how the DEFL model aptly mitigates challenges students encounter in grasping specific content—tailored educational strategies derived from pre-tutorial surveys induced marked enhancements in students' understanding across diverse knowledge spheres. Impressively, students who initially perceived their comprehension as subpar saw marked elevation in their subsequent test outcomes, attesting to the model's aptitude in bridging individual learning deficits. A juxtaposition of average grades between DEFL-engaged cohorts and others further accentuates the model's merit in uplifting academic prowess. Incorporating Learning Analytics into the Flipped Classroom, epitomised by the DEFL model, equips tutors to pinpoint and aid lagging students promptly, fostering enhanced academic pathways. While this research extols the virtues of the DEFL model, it concedes its constraints, notably the prerequisites for tutor training and fine-tuning data aggregation and evaluation procedures. Prospective studies might heighten tutor participation in the DEFL blueprint, refine integrations with academic management platforms, and hone data examination techniques. In essence, marrying Learning Analytics with the Flipped Classroom via the DEFL model heralds a pioneering and potent strategy for ameliorating student academic results. This research heartily endorses the wider adoption of the DEFL paradigm in academia, providing tutors with an invaluable instrument for refining their pedagogical approaches and augmenting student understanding in today's dynamic academic realm.

When juxtaposing the insights from the DEFL model with extant scholarship on Flipped Classroom modalities, Learning Analytics, and individualised education, notable confluences and breakthroughs surface, underscoring this research's import.

Flipped Classroom Modalities:

While traditional Flipped Classroom tactics centre around transposing the standard educational model—introducing students to new topics outside classroom confines and deep-diving into classroom applications—these methods have been commended for catalysing student participation, fostering proactive education, and deepening comprehension. The DEFL model, enriched with Learning Analytics, offers an enhancement. By decoding learner-centric data, the DEFL model seeks to pinpoint students at potential risk in a Flipped Classroom milieu sooner than conventional means might detect. Ergo, beyond extolling the standalone merits of the flipped mechanism, this DEFL-centric research melds it with data analytics to elevate the academic journey further.

Learning Analytics:

Characterised by data-centric processes like measurement, collation, evaluation, and dissemination focused on learners and their milieu, Learning Analytics aims to comprehend and elevate education. Prominent studies, exemplified by Hwang *et al.* (2017) [25] [26], have highlighted Learning Analytics' transformative potential. The DEFL model harmonises with this scholarly corpus, spotlighting data-driven insights linked to learner demographics and scenarios. However, the DEFL model's standout feature is its organic fusion with the Flipped Classroom ethos—a synergy less traversed in prior scholarship. This innovative blend heralds a more anticipatory, reactive, and customised academic environment, especially concerning early-stage interventions for faltering students.

Individualised Education:

Rooted in the conviction that educational experiences should be custom-fitted to students' unique requirements, precedent studies, such as those by Liu *et al.* (2017) [36], have demonstrated the marked advantages of bespoke learning pathways and feedback. The DEFL model resonates with this philosophy, accentuating the essence of tailored initiatives derived from data insights. Nevertheless, the DEFL's singular offering is its application within the Flipped Classroom ecosystem. Fusing bespoke education tenets with data analytics, the DEFL framework furnishes educators with an enriched, data-informed methodology to sculpt tailored academic experiences within the flipped ambit.

In summary, while individual concepts like the Flipped Classroom, Learning Analytics, and tailored instruction are already established, the DEFL model's innovative amalgamation of these fields provides fresh insights. It bridges literary voids by demonstrating the integrative potential of these methodologies to bolster student outcomes. Thus, the DEFL model emerges as a beacon in the ever-evolving pedagogical landscape, underscoring the primacy of data-informed strategies in crafting optimised and tailored educational experiences.

Conflicts of Interest

The authors declare no conflicts of interest.

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