Does blended learning hinder underprivileged medical students' academic performance?

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Abstract

Whilst the blended-learning method, a form of digital education, can increase the quality of medical schools in Indonesia, it faces significant challenges when engaging with diverse students across digital divides and with varying socioeconomic disparities.

We aimed to discover whether blended-learning will disadvantage the underprivileged medical student by exploring the correlation between 3 groups of variables: A, B, and academic performance. We compared the variable in group A with variable group B in terms of each variable group’s effect on the students’ academic performance.

Group A consists of 7 variables associated with digital divides and socioeconomic disparities measured through a survey. Group B consists of 5 variables relating to online-learning engagement and is measured through platform analytics. The academic-performance variables are measured by Readiness Assessment Test (RAT).

The sample includes 46 clinical-year medical students who are involved in a designed blended-learning curriculum. The RAT has bivariate and multivariate associations with two variables in group B: (1) the first login and duration of access, (2) the RAT has a multivariate association with the first login and duration of access. We do not find any association among any other variables in Group A or Group B with regards to academic performance.

A student’s engagement in online learning has a more direct association with their academic performance than to other variables related to the digital divide and socioeconomic disparities. Students who procrastinate in starting to access online lessons are more likely to have a weaker overall performance.

Keywords: Blended-learning; Technology-mediated instruction; Digital divides; Learning management system analytics; Medical education.
Introduction

The divides among medical students

The most influential factors of educational inequality in Indonesia are the poverty rate and income disparities which exist between individuals and regions. Around 40% of Indonesians make under USD 2 per day (Azzizah, 2015).

Computer literacy and ownership among medical students in developing countries are varied – 22.9% of students do not have a personal computer (Robabi and Arbabisarjou, 2014). In 2012, the respective rate of ownership for computer and mobile phones in Indonesia was merely 15% and 84%. With regards to computer literacy, the familiarity and ability to use hardware scores low while internet familiarity scores high. A factor that affects those scores is the number of previous computer lessons (Robabi and Arbabisarjou, 2014).

The internet divide correlates with the disparity of communication infrastructures (i.e. electricity, landlines, mobile coverage, transceiver station, cyber cafe access), spending rates, educational attainment rates, and wealth (i.e., the national Gini index and poverty rate) (Suwarwoto and Tampubolon, 2016). In China, there are significant differences in the proportions of internet use among medical school student groups. Namely, the rate of internet use for doctoral candidates is 73.5%, while the rate for undergraduate medical students is only 14.1% (Yang et al., 2014).

Internet access can help and distract a student's learning activity. An increased level of access to the internet, as seen in Jakarta, may benefit student's learning. Conversely, the rate of internet addiction among medical students is not negligible and may hinder learning; around 11.5% % of medical students in Chile, a developing nation like Indonesia, exhibit a significant score on the internet addiction test (IAT) (Berner et al., 2014).

The inequality of access to education has an adverse impact on income distribution and vice versa (Wicaksono, Amir and Nugroho, 2017). This is not exclusive to students outside of medical school. Even if medical students' academic expenses are sponsored by scholarships, living expenses are borne by the students themselves. There is still a chance that a medical student will not be equipped with electronic devices needed for learning purposes.

A student's gender, age, and finances affects their internet usage and habits in Jakarta. Statistics reveal that most Indonesian health professionals use on-campus internet access because it is free of charge. A recent study focused on medical students in Indonesia determined that the internet (mostly used for lecture references) was only accessed 1-2 times a week (Dewi and Nurhidayah, 2012).

Despite variation in diverse internet habits/familiarity, medical students displayed: (1) high interest in using new technology (Khalifian et al., 2013) and (2) an increased satisfaction level when using a familiar search engine. Relevant studies evince the strong inclination of medical students accepting such technologies in developing countries (e.g. Indonesia) (Sandars and Schroter, 2007).

This study defines the underprivileged student as a student who has at least one of the following criteria: 1. Low spending; 2. Owning fewer gadgets; 3. No home internet; 4. Long daily commuting; 5. Low internet habit; 6. Less familiar with technology; 7. Less comfortable in using technology.

Blended learning

Most of the current medical curriculum in Indonesia only includes the didactic frameworks, rather than preparing students for practical application. However, adding another formal course to focus on higher levels of Bloom's taxonomy of educational objectives will pose an additional burden for both faculty and students. Consequently, the course should be improved to improve a student’s conceptualization skills without adding more classroom time and
consuming more student and faculty energy as they engage in exhausting clinical work. Innovative approaches such as blended learning may provide a foundation and strategy for developing potential solutions (Prasetya, Wardhani and Khairani, 2016). From 6 meta-analysis and two systematic literature reviews, we can glean that blended learning outperforms fully face-to-face or fully online-learning modes (Siemens, Gašević and Dawson, 2015). Blended learning will allow to ripen conceptualization with less classroom times. Online learning will prepare the students in lower Bloom’s taxonomy, and face-to-face session will ripen the student’s conceptualization in higher taxonomy.

How well do the diverse students of an Indonesia medical school perform through blended learning? How are the associations between the variable group A (See Figure 1) with academic performances compared to the variable group B with academic performances?

**Figure 1:** Variables in its theoretical and hypothetical structure

**Methods**

This study explores the correlations between a student’s academic performance, socioeconomic background (i.e. their gadget ownership, internet availability, monthly expenses, commuting time to school), internet habits, technology familiarity & comfortability level, and online-learning engagement in blended-learning environment in Indonesian medical school through surveys, learning management system (LMS) analytics, and class assessments.

*Ethics statement*

This study was reviewed by the Institutional Review Board at Harvard University on 11/19/2018 and was deemed exempt.
In this project, we measured the academic performance of the students based on their test scores. With various assumptions of the outcome's average, outcome's standard deviation, type I error rate, and that the linear regression would be used to assess associations, we calculate that the sample size will be at least 40 students to have the 97-99% power to detect mean differences of both groups.

The intervention’s target was a dermatology clinical rotation at the Faculty of Medicine, Universitas Indonesia (FKUI). The research was conducted with 46 international medical students in FKUI in Jakarta who are enrolled in a dermatology clinical rotation. We studied 2 cohorts (January 2019 and February 2019) which consist of 46 students. This study was aimed to be generalizable to the international medical student population.

Our inclusion criteria were 5th-year medical students who are in a dermatology clinical rotation during the research time period and have not previously taken the dermatology rotation. Our exclusion criteria were students who are not engaged in at least one part of the study plan: online learning, face-to-face session, survey, and RAT.

Operational Steps
Participating students studied in a blended-learning environment. There were three sources of data: surveys, analytics, and examinations. The analytics was extracted from a native LMS of FKUI, the Student Centered e-Learning Environment (SCeLE). Then, the data was analyzed through multiple regression using STATA.

There were two cohorts of students. Each student cohort attended a dermatology clinical rotation for four weeks. On day 1, informed consent and survey were collected from the samples. Online-learning analytics were collected throughout the online part of blended-learning. On Day 3. The RAT result was collected.

The survey
A survey (See Supplementary File 1) was given to the participating students measuring their level of comfort, digital skills, information about their accessibility to the internet, backgrounds, etc. The survey was completed in a classroom of FKUI and administered by paper.

There were 23 survey questions completed by each participant which were turned into 7 variables; (1) average monthly spending; (2) daily commuting time; (3) home internet availability; (4) number of gadgets owned (4 questions); (5) level of technology familiarity (4 questions, the results ranged between 0 and 4); (6) level of technology comfortability (6 questions, Likert scale 1 to 5, the results range between 6 and 30); (7) level of internet habit (5 questions, Likert scale 1 to 5, the result is ranged between 5 and 25).

The average monthly spending variable was obtained in thousands of IDR and then converted into millions of IDR in the dataset. The daily commuting time variable was written in the time unit of hours in the dataset. The home internet availability variable was written in the dataset as ‘0’ for those students who do not have home internet and ‘1’ for those students who do have home internet.

The LMS analytics
The analytics of the online-learning platform informed the participants’ learning engagement variables. From the analytics, there are five variables: (1) page views, (2) access duration, (3) login times, (4) time of first login, and (5) time of last login. For the data collection method, please refer to Supplementary File 2.

The online-learning component contained 5 videos, including introduction video; 800-word introduction guides; 4 compressed downloadable learning materials and assignments, 3 reading materials were compressed into 1 of those
files; and 1 podcast. If a student views and downloads every piece of material once, we anticipated that it will take at least 10 ‘page views’ and around 30 minutes ‘duration of access.’ We anticipated that a student would take about 2 hours total to complete all of the assignment and read the supplemental materials; however, the exact duration is very hard to capture precisely in the online-learning analytics.

The LMS was based on Moodle technology. One of the variables collected is home internet availability. This specific platform does not have a mobile version, so students must access the platform on a PC or laptop. Therefore, most students needed to have an internet connection to access the learning platform.

The academic performance measurement
The RAT measures a student’s first performance after the online part of blended-learning. The examinations’ question sets were obtained from FKUI and were based on the student’s regular coursework.

The scores were gathered from the readiness assessment test (RAT) using multimodality questions: a combination of multiple choices, short answer, and matching questions. In order to get the best results, students were encouraged to effortfully participate on the test and we incentivized the best performer on the test with a gift. Students were also informed that the formative assessment provides a chance for them to calibrate their knowledge. Students were required to sign an honor code or statement of academic honesty before each test.

The analysis plans
Some of the data was categorized into new variables. For example, we formed two students’ groups: 1. Students who spend more than 5 million IDR a month; 2. Students who spend under 5 million IDR a month. Using Microsoft Excel, we calculated the number of samples from each group and included its percentage. Using STATA, we ran 12 linear regression analysis for all 12 predictors (7 variables from group A and 5 variables from group B) and one outcome (academic performance). Afterwards, those variables that have associations with the outcome were taken into a bivariate model and a multivariate model of regression analysis.

Results/Analysis
Data collection occurred from January 2019 to March 2019. The dataset was collected from 46 qualified samples. The dataset was written in Microsoft Excel and summarized using STATA. We analyzed 14 variables in order to find each variables’ mean, standard deviation, median, minimum value, and maximum value.

The survey results
Based on the survey (see Table 1), on average, a student spends IDR 4,610,000.00 (USD 320.00) a month for all expenses aside from lodging. For the sample, student spending varied from 1 to 10 million IDR per month. Some students lived with their parents, and some students needed to rent a dormitory or apartment. In Jakarta, the minimum wage is set at IDR 3,900,000.00 (USD 275.00) per month. With the average lodging cost ranging from IDR 2,000,000.00-5,000,000.00, students would have to spend almost two times Jakarta’s minimum monthly wage on lodging each month.

On average, students would spend 1.26 hours commuting from home to school and back every day. Commute times varied for students. For students who rented a room or apartment nearby, their daily commute time could be as short as 15 minutes per day, while the student furthest away spent four hours commuting each day. While some students calculated their commuting time based on Google Maps, other students recalled their commuting time. While estimating one’s commute time from recollection can be accurate for those who travel by a commuter line train, which has constant duration of commute every day, for students who commute by car, every day the situation can be
different which may affect their commuting duration.

Table 1: Results summary

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptive</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly spending (in million IDR)</td>
<td>4.61(2.11)</td>
<td>4.4</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Daily commuting time (in hour)</td>
<td>1.26(0.96)</td>
<td>1</td>
<td>0.25</td>
<td>4</td>
</tr>
<tr>
<td>Home internet availability (Y/N:0/1)</td>
<td>0.76(0.43)</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of gadgets owned</td>
<td>3.61(1.70)</td>
<td>3</td>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>Level of familiarity (Range: 0-4)</td>
<td>1.63(1)</td>
<td>1</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Level of comfortability (Range: 6-30)</td>
<td>22.39(3.42)</td>
<td>23</td>
<td>10</td>
<td>28</td>
</tr>
<tr>
<td>Internet habit (Range: 5-25)</td>
<td>15.46(2.1)</td>
<td>15.5</td>
<td>10</td>
<td>21</td>
</tr>
<tr>
<td>Number of page view</td>
<td>17.28(7.15)</td>
<td>15</td>
<td>9</td>
<td>44</td>
</tr>
<tr>
<td>The time of first login (in hour, from 8am of first day)</td>
<td>8.65(9.6)</td>
<td>3</td>
<td>1</td>
<td>36</td>
</tr>
<tr>
<td>The time of last login (in hour, from 9am of the last day of online learning access)</td>
<td>6.26(5.95)</td>
<td>3</td>
<td>0</td>
<td>23</td>
</tr>
<tr>
<td>The duration of access (in minute)</td>
<td>74.89(30.72)</td>
<td>74.5</td>
<td>12</td>
<td>148</td>
</tr>
<tr>
<td>Number of login attempt</td>
<td>5.09(2)</td>
<td>5</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>RAT (Range: 0-100)</td>
<td>45.43(12.07)</td>
<td>46</td>
<td>23</td>
<td>73</td>
</tr>
</tbody>
</table>

The comfortability level is measured through 6 questions (Likert scale 1-5). The average level of comfortability is 22.39 out of 30. On average, students feel comfortable using SCeLE and other LMSs. They feel very comfortable using the internet and gadgets. Only one student (2%) did not feel comfortable using the internet or gadgets. Also, on average, students feel less comfortable troubleshooting software and hardware problems on their computer. The lowest comfortability level in the sample is 10 which means that one student felt very uncomfortable on 4 out of the 6 questions related to technology use. The highest comfortability level is 28 where a student felt comfortable with all of the 6 questions.

The earliest first access to the platform is 8am on the first day. Most of the students (43%) start to access it as early as 8am on the first day. Around 15% access it around 9pm on the first day; 13% of students access it on the second day or later. Other students start to access the platform on the first day at another time (outside 8am or 9pm).

On average, students access was a time duration of 74.89 minutes, which is more than twice the expected access duration. Access varied between 12-148 minutes. Approximately 56% of the students access time was around 61-90 minutes.

The examination
The LMS’ statistics featured facility index and discriminative efficiency that showed the examination’s questions are considered excellent. The average score of the RAT is 45.43 out of 100, and scores varied from 23 to 73.
The findings from bivariate and multivariate analysis

We have 12 predictors variable and 1 outcome. After we analyze all the variables using regressions (see Table 2), we categorize the predictors, and run other regressions of the new categorized predictors. From 12 regressions, we found 4 interesting findings.

First, the RAT has bivariate associations with the students who start to access the online learning at 8am or 9pm on the first day. The students who start access on 8am on the first day tend to have 14.1 score higher ($p=0.011$, $R^2=0.119$) than those who start on the second day. The students who start access on 8am or 9pm on the first day tend to have a 9.9 score higher ($p=0.005$, $R^2=0.148$) than they who start at a different time.

Second, the students whose duration of access is more than 90 minutes tend to have 6.4 points ($p=0.027$, $R^2=0.213$) higher than the students whose duration of access is between 61-90 minutes. The students whose duration of access is less than 60 minutes tend to have 14.5 points ($p=0.001$, $R^2=0.213$) higher than the students whose duration of access is between 61-90 minutes.

Third, from the multivariate models of RAT analysis, the students who started access on 8 am or 9pm on the first day tend to have 8.7 score higher ($p=0.006$, $R^2=0.329$), and tend to have additional score of 8.0 ($p=0.031$) if they access between 90-148 minutes or additional score of 13.4 ($p=0.001$) if they access less than 60 minutes, compared to those who start to access on the other time with 61-90 minutes duration of access.

Who are the students of ‘8am or 9pm’?

Students who start to access at either 8am or 9pm have better RAT compared to students who logged on at either of those specific times. Looking deeper into this phenomenon, there were indicators identified that may explain the discrepancies of RAT between the two groups (refer to Table 3).

One indicator is comfortability level. There was a trend that students in the ‘8am or 9pm’ group (25.9%) have higher comfortability level compared to the other group (5.3%), though this finding was not statistically significant ($p =$

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Table 2: Associations of selected predictors to RAT (n=46)

<table>
<thead>
<tr>
<th></th>
<th>Bivariate models</th>
<th>Multivariate models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>SE</td>
</tr>
<tr>
<td>RAT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>First login</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Any other time (reference)</td>
<td>41.3</td>
<td>7.3</td>
</tr>
<tr>
<td>1st day, 8am-9am or 9pm-10pm</td>
<td>58.7</td>
<td>7.3</td>
</tr>
<tr>
<td>Duration of access (in minutes)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>61-90 (reference)</td>
<td>56.5</td>
<td>7.4</td>
</tr>
<tr>
<td>91-148</td>
<td>23.9</td>
<td>6.4</td>
</tr>
<tr>
<td>0-60</td>
<td>19.6</td>
<td>5.9</td>
</tr>
<tr>
<td>F3</td>
<td></td>
<td>7.1</td>
</tr>
</tbody>
</table>
The other indicator is higher spending. There was a trend that students in the ‘8am or 9pm’ group (40.7%) have higher spending (5-10 million IDR a month) compared to the other group (15.8%), (p=0.08).

Table 3: The indicators of student who start to access on 8am or 9pm on 1st day

<table>
<thead>
<tr>
<th>The Indicators: 1. Very High Comfortability Level</th>
<th>First login: Any other time (n=19)</th>
<th>First login: 8am or 9pm of 1st day (n=27)</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>n</td>
<td>%</td>
</tr>
<tr>
<td>10-25 out of 30</td>
<td>94.7</td>
<td>74.1</td>
</tr>
<tr>
<td>26-28 out of 30</td>
<td>5.3</td>
<td>25.9</td>
</tr>
<tr>
<td>2. Higher Spending</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-5 million IDR monthly</td>
<td>84.2</td>
<td>59.3</td>
</tr>
<tr>
<td>5-10 million IDR monthly</td>
<td>15.8</td>
<td>40.7</td>
</tr>
<tr>
<td>3. Shorter Commuting Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 minutes – 4 hours daily</td>
<td>68.4</td>
<td>44.4</td>
</tr>
<tr>
<td>15 - 30 minutes daily</td>
<td>31.6</td>
<td>55.6</td>
</tr>
<tr>
<td>Indicators Count:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>26.3</td>
<td>22.2</td>
</tr>
<tr>
<td>Exactly 1</td>
<td>57.9</td>
<td>51.9</td>
</tr>
<tr>
<td>Exactly 2</td>
<td>15.8</td>
<td>18.5</td>
</tr>
<tr>
<td>Exactly 3</td>
<td>0.0</td>
<td>7.4</td>
</tr>
</tbody>
</table>

Discussion

The purpose of this study is to find whether the digital divide and socioeconomic disparities affects a student's performance in a blended-learning environment. The students in this study had at least one computer to access the platform, a certain level of internet connection speed, knowledge to operate a computer and navigate the online learning platform, and a certain comfortability level on learning through the online platform. The SCeLE training by the university ensures all requirements are fulfilled.

This study is limited in that the medical students in rural or newly established medical schools in Indonesia may not have fulfilled all requirements. Students in an underprivileged medical school may not have sufficient internet access because the infrastructure has not been built. Although students may receive a laptop from the school/local government if they do not own a computer, their lack of familiarity with the device may hinder their learning.

This study is aimed to be generalizable to its targeted population, international medical students. However, this study includes only 46 students, which may affect the range of its generalizability. The population to whom this study may be generalizable to are medical students who own at least one phone and one computer, internet connection, and can access/navigate the online platform.

The RAT score has an association with a student’s first login and duration of access. The student who procrastinates is more likely to have a lower score. The students who access the online platform at a specific hour (8am or 9pm) for
their first login and for a specific duration of access (< 60 minutes or > 90 minutes) tend to have a higher score. The purpose of this study is to investigate the validity of incorporating blended-learning as a learning tool. Like all learning tools, the student retains the agency in their individual pursuit of academic excellence. This study reveals an encouraging result that, regardless of comfortability/familiarity in technology or socio-economic background, positive results are correlated to a responsible learning engagement.

The workload in this blended-learning environment is heavier than what students usually face in an online learning platform based on their prior experiences in medical school. They usually use an online learning platform as a peer-to-peer sharing platform where they can download the materials and assignments and finish them offline. An early login can be a presumed indicator of effective time-management/prioritizing assignment (e.g. worksheets, thought questions etc.), and late logins usually result in the opposite.

The students whose duration of access is less than 60 minutes have the highest average score compared to the group with duration of access more than 60 minutes. However, the number of login times can only predict the range of online learning but cannot provide a precise and exact duration of students’ access (e.g. difference in 60 minutes between two logins may mean using the online platform from anywhere between 60-120 minutes, as LMS automatically logs out every 30 minutes). Since there was no correlation between the duration of access and the number of login times, we proffer that the students who access less than 60 minutes may already have had stronger preliminary knowledge about the content before the online session.

Although the students have 49 hours to access the online learning, 43% of the students in the sample access it as early as possible. Approximately 78% students in the sample who start to access the platform at the specific time of 8am or 9pm have at least one following indicator: a very high comfortability level, higher spending, and shorter commuting time. This shows that the literacy, socioeconomic background, and internet habit will not directly affect a student’s score. The indirect effect of those variables is based on the student’s decision to access it earlier and not procrastinate.

More importantly, this study shows that the academic performances are associated more with Group B (student’s level of online learning engagement) rather than Group A (their socioeconomic-related background or literacy level). The low R-squared in this study (9.8-33%) showed that the model explains just a little response variability. However, that result was statistically significant (alpha = 0.05) and considered ‘normal’ in educational research which attempts to assess human behaviour.

**Conclusion**

The online part of blended learning, thus, will not disadvantage the underprivileged medical student’s academic performance.

**Take Home Messages**

The online part of blended learning, thus, will not disadvantage underprivileged medical student’s academic performance in a case that:

- The students in this study had at least one computer to access the platform, a certain level of internet connection speed, knowledge to operate a computer and navigate the online learning platform, and a certain
comfortability level on learning through online platform.

- The SCeLE/ Learning Management System training by the university ensures all requirements are fulfilled.

Notes On Contributors

**Dr. Nanda Lucky Prasetya** is an alumni of Master of Medical Sciences in Medical Education of Harvard Medical School (HMS), and also a principal investigator of this research. His work and career is related to the intersection of digital, education, and healthcare. This research is a part of thesis project at HMS and a collaboration with Universitas Indonesia, where the majority part of the research was done.

**Dr. Sri Linuwih Menaldi**, a dermatologist-consultant, senior lecturer of dermatology in Universitas Indonesia, and an alumni of doctorate program in medical education of Universitas Gadjah Mada.

**Dr. William Wisser**, a Director of Teaching and Learning Lab at Harvard Graduate School of Education.

**Dr. Michael Parker**, an Associate Dean of Online Learning at Harvard Medical School (HMS) who leads HMX, an HMS' online learning platform.

**Cheuk Pui Kwong**, a penultimate law student from Durham University, United Kingdom, who is passionate about pursuing a career in law education, an in-depth linguistic reviewer and proofreader of this paper.

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Figure 1 – Source: Nanda Lucky Prasetya.

Bibliography/References


**Appendices**

None.

**Declarations**

The author has declared that there are no conflicts of interest.

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**Ethics Statement**

This research was considered by Harvard Human Research Protection Program at Harvard University on 19 November 2018 and deemed exempt because this research meets the criteria for exemption per the regulations
found at 45 CFR 46.101(b)(1)(2). The research was conducted in accordance with the Declaration of Helsinki. Additional information can be found at:
https://cuhs.harvard.edu/files/cuhs/files/urtp_curriculum_-_student_guide_dec_20171.pdf and

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