The Link between Internet Connectivity and Missed Assessments in the Online Class Modality

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Abstract

Many published papers provide insights on factors affecting learning performance; however, they do not address how internet connectivity affects students' capacity to meet assessment and learning expectations. To address this gap in the literature, we draw from a survey of 257 students at the undergraduate level to investigate two questions: (a) To what extent does internet connectivity affect missed assessments? and (b) How do students vary through the distribution of missed assessments? We used a count data model, specifically, negative binomial (NB) regression, to determine incidence rate ratios and odds of missed assessments. The NB results showed that students who indicated poor internet connectivity during the semester had about a five times higher incidence rate of missed assessments than students who did not indicate poor internet connectivity. Surprisingly, despite two-thirds of students reporting poor internet connectivity, the chance of accumulating seven missed assessments during the semester was very minimal. The results may provide insights to faculty and education policymakers at the institutional level on ways to design online learning to meet learning expectations.

Keywords: internet connectivity, learning performance, missed assessments, online modality

Since COVID-19 was declared a pandemic by the World Health Organization (WHO) in the first quarter of 2020, there has been no shortage of research papers on how it has transformed learning in higher educational institutions around the world. Online learning in many parts of the world, especially in developing countries, faced a number of constraints, such as access to internet connectivity, financial resources to procure technological devices and physical environment conducive for effective learning (Fishbane & Tomer, 2020; UNESCO, 2020; Affouneh et al., 2020; Crawford et al., 2020; Limniou et al., 2021). Furthermore, because online learning is dependent on digital tools, many schools implemented varying digital learning activities based on resource capacity and platform limitations (Joshi et al., 2020). While there are a number of new online learning technologies available in the market today to boost both learning and delivery capacity by faculty (Goh & Sigala, 2020), many schools lack the capacity to procure these new technologies. Even when schools can afford such platforms, students may not have adequate digital devices or a conducive environment to engage faculty (Arora & Srinivasan, 2020, Agarwal & Kaushik, 2020; Chick et al., 2020).

Experiences in online modalities are not entirely negative. An expansive body of research shows positive effects of online transition on students (Babbar & Gupta, 2021; Muthuprasad et al., 2021; Chisadza et al., 2021). Chisadza et al. (2021) identified clear opportunities with respect to the shift to online learning. Babbar & Gupta (2021) measured benefits of online learning in terms of innovations in the types of assessments used in higher education. Muthuprasad et al. (2021) explored students' preferences for various attributes of online classes including online learning environment. They found that the main attraction to online classes are flexibility and convenience brought by online learning. For the most part, it has become increasingly possible for students to get into classes from the comfort of personalized spaces.

From all indications, digital inequality, described by Beaunoyer et al (2020) as "… access to networks or connected devices, or when it comes to the skills required to navigate computerized spaces optimally" (p. 1), remains a problem for online education in developed and developing countries. Prior studies have shed light on various aspects of the problem of digital inequality: sustainability or environmental conditions in Mexico (Vargas et al., 2020); internet connectivity and socio-economic class in Ireland (Cullinan et al., 2021); internet usage and academic achievement in Indonesia (Soegoto & Tjokroadiponto, 2018); internet access and power outage in Nigeria (Ivwighreghweta & Igere, 2014); low income students and online education in India (Jain et al. (2021); limited laboratory-related courses and internet connectivity in the Philippines (Rotas & Cahapay, 2020; Cahapay, 2020); academic performance and access to WiFi in South Africa (Chisadza et al., 2021); and internet connectivity and lower remote learning proficiency in the USA (Katz et al., 2021).

There has been almost no empirical work on the relationship between internet connectivity and missed assessments except for Katz et al. (2021) which focused on the association between internet connectivity and lower learning proficiency in an online modality. Given how the education sector around the world was forced to go online and the inherent problem of balancing quality and expectations of students' compliance with online assessments, there is an important gap to fill in understanding the full range of what might be necessary in designing online learning. When many schools transitioned to an online modality, the traditional institutional guidelines governing the conduct of class were formulated for face-to-face context. Applying these guidelines without clear understanding of underlying factors driving student responses to assessments became a problem. Granting extensions to assessments submitted after a deadline in face-to-face classes is a common issue faculty deal with all the time. In online settings, missed assessments assume a different dimension because not only are digital devices needed, but also internet connectivity is required to drive the virtual meeting and facilitate timely submission of assessments. Understanding how internet connectivity is related to the number of missed assessments can serve as a reference for setting guidelines that govern expectations in online learning and outcomes as well as the administration of these assessments.

To contribute to literature, the study investigated two questions: (a) To what extent does internet connectivity increase or decrease missed assessments? and (b) How do students vary in the distribution of missed assessments? We use a count data model which allows for discrete values in regression estimation to examine the relationship between internet connectivity and number of missed assessments and analyzed odds of missing assessments. The goal is to understand a possible potential allowable number of missed assessments that students may incur in an online modality without penalty. Overall, our focus on the relationship between internet connectivity and missed assessments distinguishes our paper from the only similar work done in the US using a unique data set from 30 universities from 19 states and the District of Colombia on internet connectivity and lower Remote Learning Proficiency (Katz et al., 2021).

Prior studies have made enormous contributions to online learning in the literature especially in the area of learning outcomes; however, this study may be the first to model missed assessments of students in an online modality in higher education using a count data model. We believe that the findings appeal to a broad spectrum of online advocates, readers and educators including education policymakers.

The rest of the paper is organized as follows: Section 2 describes the data sources and summary statistics including institutional context of missed assessments, Section 3 gives the empirical strategy including detailed theoretical and empirical formulation of the estimation process, Section 4 discusses the main results, and Section 5 offers concluding remarks and draws policy implications.

Educational Setting and Data

Institutional Context of Assessments and System's Theory in Education

Assessment is a key process of learning in higher education. In fact, assessment has been described by Hodges et al. (2014) as "intrinsically linked to student learning and performance" (p. 189). Assessment as an integral part of higher education has been exhaustively studied and theorized (Hodges et al., 2014) and its role in feedback mechanisms facilitating learning has been well-documented (Graham et al., 2021). But as educational institutions transitioned from the traditional face-to-face to online classes, many schools were faced with two problems occurring simultaneously: relevant data for suitable guidelines for online classes and adequate digital infrastructure including stable internet connectivity (Chisadza et al., 2021; El Said, 2020).

There are three types of assessments that are commonly used in varying forms in online modalities: formative, enabling, and summative. Formative assessment, as the name implies, involves more frequent informal activities used in between teaching to gauge students' understanding of lectures and does not count toward grades directly. It is used to prepare students for either enabling or summative assessments (Burkhardt & Schoenfeld, 2018). Enabling assessment is periodic and more frequent compared with summative assessment.

Enabling assessment may be described as mini-summative in the sense that it gauges progress of learning on a much smaller scale at different points within the same module (e.g., consisting of few chapters). It is not uncommon to have two or three in one module depending on the subject. Examples include multiple choice questions, short essays, debate exercises, etc. On the other hand, summative assessment is usually designed to gauge overall grasp of the entire module or multiple modules and may involve written examinations, written research papers or well-designed projects (Guangul et al., 2020).

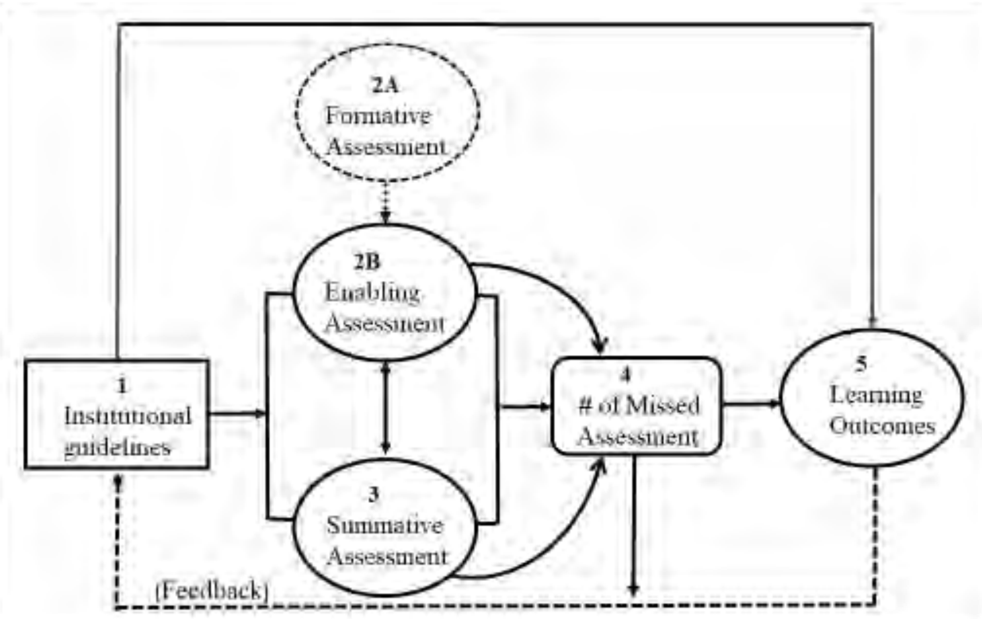
Overall, assessment has been described as a good measure of both quality and progress in online learning (Babbar & Gupta, 2021). However, even when assessments have been developed by experts to elicit a given performance, its usefulness will ultimately depend on digital infrastructure and home conditions driving communications and feedback in both directions (students and faculty) for smooth and unrestricted learning to take place (Yan & Carless, 2021). Yet not enough attention has been given to the effect of internet connectivity on students' ability to meet online assessment expectations. Assessments help faculty make better decisions on students' progress (Carless & Winstone, 2020); however, when students are unable to submit assessments in a timely manner due to poor WiFi reception or internet connectivity, faculty may apply penalties indiscriminately which is contrary to how the feedback mechanism should work. Kintu et al. (2017) notes that, "efficient use of a learning management system and its tools improves learning outcomes in e-learning and blended learning environments" (p. 5). Evidence of the challenges faced in an online modality due to lack of clear cut guidelines governing conduct has been documented (Guangul et al., 2020).

Our goal in this section is to situate online assessment within the literature of learning outcomes using general systems theory applied to education to inform our empirical strategy in Section 3. In the conceptual framework (Figure 1), we propose that well-thought out institutional guidelines for the online modality should be informed by inputs from missed assessments in a feedback mechanism. System's Theory in Education is anchored on General System Theory (GST) founded by Von Bertalanffy in the 1930s (Drac, 2015), which has been used extensively in educational research to analyze educational output as a function of inputs at different levels (John, 2010; Garira, 2020). Systems theory acknowledges the universality of the feedback mechanism as a necessary component to achieve desired learning outcomes. Viewed through this lens, institutional guidelines become part of a school's inputs in an educational production function in which minimizing the number of missed assessments is an objective function to be achieved for desired learning outcomes to occur (John, 2010).

We denote missed assessments as the sum of enabling and summative assessments students' failed to submit on deadline during a given semester. In reality, some students may miss only one type of assessment, enabling or summative, and not necessarily both. Institutional guidelines should be formulated with a clear understanding of what these rules are supposed to address. For example, how many missed assessments can be tolerated in online modality in a given subject per semester? When and how should faculty intervene if there is a clear indication that the reason for missed assessment is not valid? These questions relate broadly to the spectrum of issues associated with formulating guidelines for effective learning outcomes.

Exhaustive discussion of factors affecting learning outcomes are diverse and complex (Malecka et al., 2020), and beyond the scope of this paper. The study's goal is to highlight that feedback mechanisms could be used to improve learning outcomes through integrating relevant institutional guidelines. Figure 1 illustrates the relationships between institutional guidelines, missed assessments and learning outcomes. When institutional guidelines are set arbitrarily, there is a possibility that they may create a ripple effect influencing enabling and summative assessments, total number of missed assessments and learning outcomes

Figure 1
Proposed Relationship between Institutional Guidelines and Missed Assessments with Feedback Mechanism



As shown in Figure 1, formative assessment does not count toward grade and is assumed to influence enabling assessment indirectly because many faculty members do not incentivize its completion. It is used to prepare students for graded assessments such as enabling or summative. Guangul et al (2020) noted that, "formative and summative assessments in conjunction with appropriate feedback systems are used to support learning in higher education" (p. 521). Our framework (Figure 1) depicts the possible interplay between enabling and summative assessments. The double-headed arrow indicates that enabling assessment may influence summative assessment, and can itself be influenced by summative assessment. This is primarily because a missed assessment is assumed to be cumulative, that is, inability to submit an enabling assessment may influence submission of a summative assessment and vice versa. As shown in Figure 1, the feed forward from [1] through [4] to [5] may occur in an environment where institutional guidelines are set arbitrarily. The dashed line depicts a system which provides for a number of missed assessments to be used as input for policy changes at the institutional level through a feedback mechanism. In case of well-thought out guidelines, the possibility of [1] to [5] upper loop may be realized on efficiency grounds due to the absence of impeding factors. Additionally, the feed forward from [1] through [4] to [5] may be improved as well using a feedback mechanism. The proposed conceptual framework can be used to understand a system in which minimizing the number of missed assessments and improved learning outcomes are objective functions. An empirical link between missed assessments and internet connectivity may provide the starting point in addressing policy changes at the institutional level. We describe our data set and present summary statistics below.

Data Source and Summary Statistics

This study was based on the data collected from 257 undergraduate students enrolled in online classes at a private university in the Philippines during the second semester of school year 2020-2021. The student participants were from two colleges (Education, CE and Business Administration, CB) covering 4 programs (Education, Economics, Finance and Entrepreneurship). The two colleges were selected based on the professors' willingness to join the study and ability to handle the challenging data collection process. Participating faculty teach courses with term papers (with well-defined rubrics for evaluation) as part of the final requirement. The rubrics used to evaluate the final requirement were comparable across programs to reduce instructional heterogeneity.

Internet connectivity was measured through student binary answers [yes or no] to the question: Have you missed an assessment deadline or online class due to poor internet connection? The number of missed assessments was measured through the question: How many times in the last semester? The actual number of missed assessments and performance scores on the final class requirement were generated from class records downloaded from the online platform**.** Students were given at least one week to submit assessments. The online platform prevented submission after the deadline**.** Other characteristics, such as personal and family background were collected from students using survey questionnaire forms. Data collection was approved by the University's Ethics Review Committee. As expressed in the informed consent document, participation in the survey was voluntary and included a statement regarding the right of students to withdraw at any point during the data generation process without consequences. There were no incentives given to any student for answering the questionnaire to avoid undue influences and to minimize errors. Table 1 reports the definitions of socio-economic and demographic characteristics of student participants.

Table 1
Definition of Variables used in the Analysis

Variable name	Definition
Dependent variable	
Missed Assessment*	Number of missed assessments
Explanatory variables	
Internet connectivity	Students who reported to have missed assessments due to poor internet connection, value=1 if yes,0 otherwise
Team participation	value =1 if the output is solo, 0 otherwise
Performance	Final score on paper
Age	Age of respondent
Household size	Number of people in the household
Gender	value =1 if respondent is male, 0 otherwise
Study hour	Number of hours per week in studying
Father's Employed	value =1 if employed, 0 otherwise
Mother's Employed	value =1 if employed, 0 otherwise
Father's Education	value =1 if college graduate, 0 otherwise
Mother's Education	value =1 if college graduate, 0 otherwise
College of Business (CB)	value =1 if home college is Business, 0 otherwise
College of Education (CE)	value =1 if home college is Education, 0 otherwise
Job	value =1 if student has a part-time job, 0 otherwise
GPA	Current Grade Point Average (as of last semester)
Team preference	value =1 if student always prefer individual work not group, 0 otherwise
Electricity bill	Estimated cost of family electricity bill per month

Note. *Summative and enabling assessments submitted after deadline

Table 2 reports descriptive statistics of students who participated in the study. The average number of missed assessments was 2.6 (SD = 3.04), but ranged from 0 to 15. The minimum number of graded assessments in a given semester was 12 (4 summative and 8 enabling). Assessments were structured to ensure that one assessment did not carry too much weight in the final grade. Formative assessments were not graded, but were commonly used by faculty to provide students with an opportunity to practice skills as a lead-in to both enabling and summative assessments. About 66% of students reported having poor internet connectivity, while 34% did not report experiencing poor internet connectivity.

Table 2
Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Poor internet connection (yes)	0.66	0.47	0	1
Number of missed assessments	2.60	3.04	0	15
Gender (male)	0.31	0.46	0	1
College of Business (yes)	0.79	0.41	0	1
GPA	3.35	0.64	1	4
Working student (yes)	0.19	0.67	0	8
Preference for group output (yes)	0.67	0.46	0	1
Father is college graduate	0.63	0.48	0	1
Father has a job (yes)	0.79	0.40	0	1
Mother is college graduate	0.68	0.46	0	1
Mother has a job (yes)	0.59	0.49	0	1
Study hours/week	23.88	20.52	1	120
Household size	5.21	2.53	0	26
Electricity bill (monthly)	4375.48	2982.83	600	18000
Age	19.65	1.77	15	35
Performance (Avg.score final paper)	88.76	7.37	70	97
Solo (individual output = yes)	0.52	0.50	0	1

Note. Monthly bill expressed in Philippine pesos (US$1=Php50).

Theoretical and Empirical Strategy

Formulation of Missed Assessments

Examining the link between internet connectivity and missed assessments presents special econometric challenges. First, the number of missed assessments by students is a count variable, therefore, treating it simply as continuous variable and applying linear regression will result in biased estimates and may be improved using a count model such as Poisson (Greene, 2003). Second, using the Poisson model does not guarantee unbiased estimates. This is because missed assessments may not conform to the restrictive nature of the Poisson model. Greene (2003) points out, “Poisson has been criticized because of its implicit assumption that the variance equals its mean” (p. 743). Assessments are typically cumulative, missing one assessment increases the chance of missing another assessment as course requirements progress over the duration of the semester. This may explain why the independence assumption of the Poisson model is often violated (Sturman, 1999; Wooldridge, 2002).

To address this challenge, we first modeled missed assessments using the restrictive Poisson model to assess whether missed assessments conform to the standard Poisson’s assumption which states that the of mean of missed assessments must equal its variance. Preliminary analysis of the data indicated that the Poisson model did not apply. If the Poisson model was applicable, it would imply that missing one assessment does not necessarily increase the chances of missing another assessment. In reality, our data analysis implied that it does, meaning that a less restrictive model like negative binomial is more appropriate for analyzing missed assessments.

Negative binomial is less restrictive and allows for the possibility that variance of missed assessments can exceed the mean (Yirga et al., 2020). We modeled the number of missed assessments of each student (y_i) in the four programs during the semester using a negative binomial model, which is assumed to take nonnegative integer values (i.e., 0 or greater than zero). We assumed that y is a random variable which shows the number of times students have missed assessments during the second semester, school year 2020-2021. The maximum likelihood estimator using the Poisson distribution is used to estimate the mean. Essentially, we are looking for the mean (lamda, λ) of missed assessments given the number of assessments (y_i) missed by each student during the second semester. This problem can be said to follow the Poisson distribution and each missed assessment has a Poisson distribution expressed as $y_i \sim$ Pois (λ). The probability density function (PDF) of each missed assessment given the mean parameter (λ) can be formally expressed in equation 1 including all relevant equations used in the estimation process (Appendix 1). Our primary specification related the number of missed assessments (y) to other explanatory variables ($x's$) in which the key variable is internet connectivity shown in equation 12 (Appendix 1).

Results and Discussion

We examined the link between internet connectivity and missed assessments in two ways: differences between students reporting poor internet connectivity and those who did not report poor connectivity in our sample (Table 3) and incidence ratio (Table 4). Table 3 shows that the mean number of missed assessments among students who reported poor internet connectivity was 3.62 (*SD* = 3.12; higher than sample mean in Table 2), while among students who did not report experiencing poor internet connectivity, which was about 0.80 (*SD* = 1.81) missed assessment. The *p*-value is highly significant, which implies that between the two groups, the number of missed assessments was on average different. This first evidence provides the need for further analysis using negative binomial in Table 4.

Table 3

Comparison of students' characteristics using two sample t test

Variable	Poor Internet Connectivity				*t*	
	Yes		No			
	Mean	Std.D	Mean	Std.D		
Missed Assessment	3.62	3.12	0.80	1.81	-7.24	***
GPA	3.27	0.66	3.54	0.51	3.35	***
Study hours	22.53	18.84	26.60	23.40	1.50	
Household size	5.18	2.22	5.27	3.07	0.27	
Electricity bill	4435.6	2951.62	4290.57	3059.73	-0.36	
Age	19.79	1.88	19.37	1.51	-1.77	*
Performance	88.36	8.60	89.64	3.95	1.31	

Note. ***1% ; *10%

Table 4
Generalized binomial regression for missed assessments

Variable Missed Assessment (Count = dependent)	IRR		Std. Error	Conf. Interval (95%)	
Internet connection(poor=yes)	4.936	***	0.927	3.415	7.133
Age	1.146	***	0.064	1.027	1.281
Home College (CBAA=yes)	2.137	**	0.695	1.129	4.045
Household size	1.052	*	0.032	0.991	1.117
Study hours	0.996		0.004	0.988	1.004
Group preference (Individual = yes)	0.871		0.139	0.635	1.192
Education of father (college=yes)	1.056		0.197	0.733	1.523
Education of mother (college=yes)	1.258		0.251	0.851	1.861
Job of mother (employed=yes)	1.135		0.187	0.821	1.569
Job of father (employed=yes)	0.794		0.159	0.536	1.176
Student (parttime job =yes)	1.181		0.124	0.962	1.449
Gender (male)	1.033		0.174	0.742	1.438
Electricity bill	0.999		0.001	0.999	1.000
Constant	0.209	***	0.027	0.001	0.267
Lnalpha	-0.404		0.192	-0.779	0.084
Alpha	0.667		0.127	0.458	0.972
LR test of alpha=0: chibar2 (01);	111.49				
Prob >= chibar2	0.000				
Log likelihood	-415.952				
Number of observation	214				
LR chi2 (12)	77.87				
Prob > chi2	0.000				
Pseudo R2	0.086				

Note. ***1%, **5% and *10%

The results of our empirical link between missed assessment and internet connectivity based on equation 12 (Appendix 1) are presented in Table 4. But before evaluating the coefficients, we tested the appropriateness of the negative binomial model. As discussed in the model formulation (Appendix 1), negative binomial models assume that the conditional means are not equal to the conditional variances. To test this assumption, we used a likelihood ratio test that alpha equals zero. This test compares this model to a Poisson model. The lower left section of Table 4 shows the associated chi-squared value of 111.49 with one degree of freedom. The probability value is highly significant, which suggests that alpha is non-zero and implies that negative binomial model is more appropriate than the Poisson model.

The coefficients in Table 4 are expressed as incidence rate ratios (IRR). Results indicated a positive and significant link between poor internet connectivity and missed assessments. Students who reported to have poor internet connectivity had a 4.93 times higher incidence rate of missed assessments than students who did not report to have poor internet connectivity holding other variables constant. On average, older students tended to have higher incidence of missed assessments. To put it differently, a one-year increase in age tended to increase missed assessments by 1.15 times (or about 15%). The incidence rate of missed assessments for students from CB was 2.13 times higher than the incidence rate of students from CE. Additionally, household size tended to increase the incidence rate of missed assessments. Increase in household size by one increased the incidence of missed assessments by 1.05 times (or about 5%).

Perhaps relationships between internet connectivity and missed assessments is not surprising, given that results from previous studies in online learning have alluded to it indirectly. In particular, Joshi et al. (2020) showed that educational technologies are correlated with the level of learning outcomes. Babbar and Gupta (2021) and Allen (2015) described assessments as the key driver of quality in any educational system, and recommended requiring academic institutions to focus on the integrity of assessments. Our results not only point attention to internet connectivity as a barrier to online learning, but also highlight issues regarding expectations and compliance by students with respect to online requirements. In Figure 2 and Table 5, we revisit the problem of missed assessments through visual illustration of predicted odds given the sample of students in this study.

The findings on age indicate that missed assessments may increase with age. We found this counterintuitive since older students tend to be more mature and responsible. But, literature has also shown that students of different age categories may be interested in different sets of assessments (Aldrich et al., 2018), which may explain the differences in missed assessments. Older students may also have additional non-school responsibilities related to work and/or family. However, the link between age and missed assessments has not been explicitly examined by previous studies and may require more research to understand the mechanisms through which age affects missed assessments.

Less surprising is the incidence rate of household size and missed assessments. Though previous studies may have linked household size to an array of factors including educational goals, our interest lies on how size of household may impact the home environment setting in online modalities, which in turn may influence students' missed assessments. Household size may be associated with home factors producing concurrent mechanisms with countervailing effects. For example, an increase in household size may increase the number of people using the internet at a given time which in turn may affect internet stability especially when bandwidth is low.

To examine the probability and odds of missed assessments, we used information on mean values of missed assessments from Table 2 and a special command from *Stata* software to probe further on the number of missed assessments by students. We calculated the odds of missed assessments by students, and used the calculated probabilities to generate Figure 2, which visually illustrates the relationship between mean probability and number of missed assessments in the sample. The computation of probability and odds of missed assessments in Table 5 provides useful quantitative information. For example, there is a 7% chance of not missing assessments across all four programs in the sample, which tells us that it is possible to have zero missed assessments in a given semester. While the zero missed assessment is not impossible, it is not a realistic expectation for all students given what we know from Table 4. However, looking at the other extreme, there is only about a 1% chance of missing seven assessments in a semester. We can also examine Table 5 through cumulative probability (pcum), that is, the odds of a specific number of missed assessment. For example, the odds are about 75% that students miss at least two but no more than four assessments, with the peak at two (25% odds). We transformed Table 5 into a visual representation in Figure 2. In this representation, the vertical axis records probability ranging from 0 to a little over 25% and the horizontal axis records the number of missed assessments. As can be gleaned from Figure 2, missed assessments peaked at number two. Notice how the number of missed assessments decreases after number six missed assessments and progressively approaches zero. Figure 2 provides interesting insights regarding missed assessments and can help inform policy makers regarding the number of missed assessments that may be deemed reasonable in any given semester considering all possible scenarios including poor internet connectivity and other home factors. As Figure 2 illustrates, the 7th missed assessment lies to the right and far away from the mean of the entire sample suggesting that the probability of accumulating the 7th missed assessment is very low.

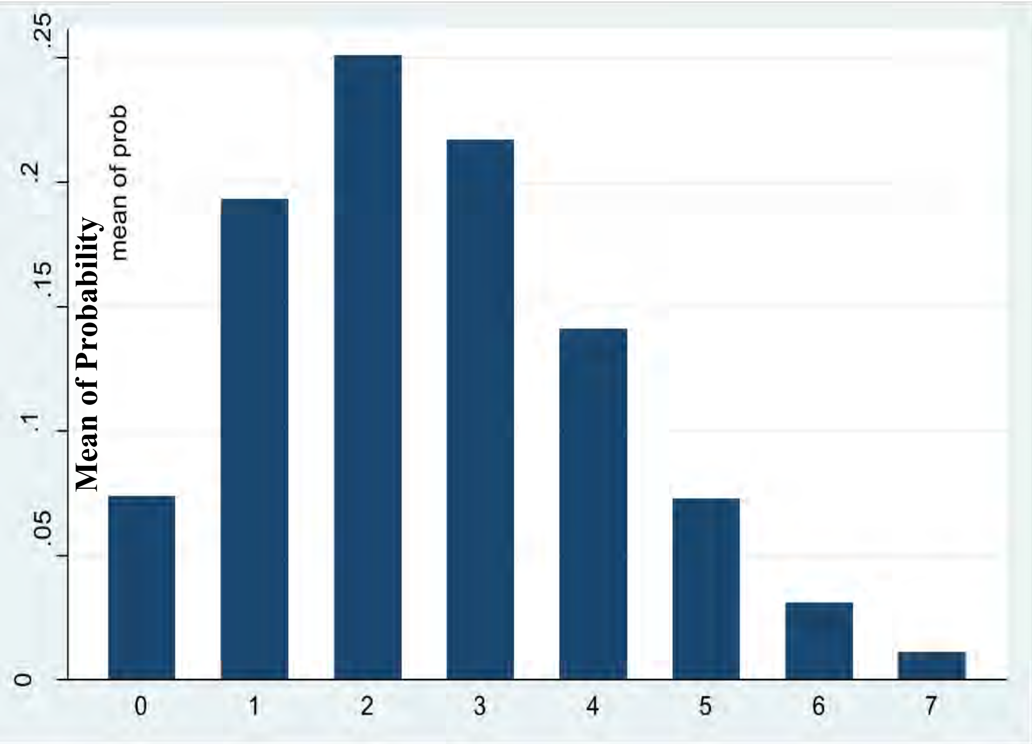
Table 5

Probability or Odds of Missed Assessments (2.6)*

** Number	Probability	Cumulative probability (pcum)
0	0.074	0.074
1	0.193	0.267
2	0.251	0.518
3	0.217	0.736
4	0.141	0.877
5	0.073	0.951
6	0.031	0.983
7	0.011	0.994

Note. *Mean of missed assessments; **number of missed assessments

Figure 2
Number of Missed Assessments with Mean of Probabilities



Suppose that an institutional policy mandates the number of allowable missed assessments during each semester to be arbitrarily set at one? This will be impractical given the underlying forces which may increase missed assessments in a given semester. However, in order to compel students to maintain a sense of responsibility and adhere to expectations regardless of home conditions, it may be reasonable to keep the number of allowable missed assessments to between six and seven beyond which some level of penalty may be assessed in the form of decreased score. Without clear-cut institutional guidelines, faculty are left with the burden of having to figure out what may constitute valid reasons for missed assignments. As shown in Figure 2, mean probabilities can help to inform institutional rules governing expectations of students in online modalities.

Conclusion, Implications, and Recommendations

The unprecedented occurrence of COVID-19 pandemic compelled educational institutions to carry out online learning modality which created challenges to school administrators, teachers, and students particularly on the effective facilitation of the teaching-learning process. As this method relies heavily on internet connectivity, the current study delved into finding the link between internet connectivity and students' missed assessments. Results revealed that there is a positive and significant link between poor internet connectivity and missed assessments. The findings also showed that other factors, such as age and household size are related to missed assessments.

Our results have broader implications for the ongoing debate about how to design effective online classes and the challenges of incorporating timely submission of assessments to aid feedback between faculty and students, and most importantly to promote quality learning.

While online class can never be a perfect substitute for face-to-face, institutional guidelines must be forward looking to allow feedback and the possibility that online classes will persist way into the future, even after the COVID-19 pandemic has ended (El Said, 2020). The analysis we have presented here suggests that a key impediment to online learning may well be institutional guidelines that fail to take into account the larger picture of underlying factors affecting students. The biggest takeaway from this research is that home environment, which includes internet connectivity, greatly influences online learning. Finding an innovative way to improve unstable internet connectivity is a key driver to promote both the quality and expectations of learning. These may appear to be overstated since quality and expectations were not directly measured in this study. In a more practical sense, the inability to summit assessments in a timely manner, hampers the feedback mechanism that reinforces learning, which in turn may affect quality of learning.

The results offer other insights. For example, the probabilities of missed assessments calculated in this study raises important questions regarding multiple claims of missed assessments given that the chances of the 7th missed assessment in a semester based on our sample is extremely small. Our results present an opportunity for school administrators and advocates of online learning to revisit rules governing the conduct and expectations in online modalities. In the second (2) section of this paper, we presented the educational context of assessments, we asked two specific questions that faculty in any online modality may confront: how many missed assessments can be tolerated in a given subject per semester or term?; and when and how should faculty intervene if there is a clear indication that the reason for missed assessment is not valid? These questions relate broadly to the spectrum of issues associated with formulating guidelines for effective learning outcomes and deserve answers. One possible approach to answering these questions might involve implementing the type of framework proposed in Figure 1. Our results provide a guide to institutional policymakers. Clearly, addressing issues regarding internet connectivity is critical to any strategy aimed at improving learning outcomes.

Nevertheless, it is important to take note of the limitations of this study. Sample size is small, therefore both robustness and generalizability of the findings may benefit from expanding the sample size of this study. Although additional information such as dates present in online classes, actual number of missed assessments, late submission of assessments and types of assessments were generated from the online platform, other diverse and complex factors such as study habits, learning attitude, digital skills, personality among others were not measured in the survey instrument. Internet connectivity responses were based on students reported experiences which we have no way of verifying in real time or during the period when assessments were given. However, the methodology and model used in this study has provided interesting insights and direction for future research. Future studies may utilize longitudinal or bigger and more representative datasets to extend and test the robustness of findings. Quasi-experimental design may help to probe further on the relationship between internet connectivity and missed assessments for different categories of students across schools.

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Appendix 1

Modeling count data, starts with the most commonly used model, Poisson regression. Following Greene (2003), the Poisson distribution with observation *i* can be expressed as:

$$\Pr(Y_i = y_i \mid x_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}, \; y_i = 0,1,2... \qquad [1]$$

where, y_i refers to missed assessment by each student in a semester, $y_i!$ is y factorial, and λ_i is lamda which accounts for the mean incidence rate of missed assessments. The most prominent assumption of Poisson is that the conditional mean is equal to the conditional variance. The variance-mean equality of Poisson distribution implies, var(y/x) = *E*(y/x). The mean parameter λ_i is related to (that is, a function of) regressors, x_i as each y_i is drawn from a sample, which is assumed to be random (i.e., independent and identically distributed). A common mean function, following Wooldridge (2003) and Greene (2003), is the loglinear model:

$$\begin{aligned} \ln \lambda_i &= x_i^{'} \beta \\ &= \beta_0 + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} = \beta_0 + \sum\nolimits_{j=1}^{k} \beta_j x_{ij} \end{aligned} \qquad [2]$$

since from equation 1

$$\lambda_i = \exp(x^{'} \beta) \quad i = 1,...,n$$

Equation 2 models each student's number of missed assessments as having a Poisson distribution where the expected number (λ) is a function of regressors and the summation sign, $\sum_{j=1}^{k}$ indicates the sum of missed assessments by all students. Equations 1 and 2 shows that Poisson model is related to negative binomial and for the most part regarded as a special form of Poisson model.

Negative Binomial (Poisson-gamma) Regression Model

The main attraction of negative binomial (NB) is its flexibility allowing for the possibility for the variance of missed assessment to be independent of the mean, which is not possible with Poisson regression model. Thus, it allows for a scale parameter to be added in the formulation to account for overdispersion in a count data (Yehia, 2021). The NB is modelled typically as a generalization of Poisson model by allowing for unobserved effect into the conditional mean. This additional parameter allows the conditional variance to be greater than the conditional mean, which accounts for overdispersion. This can be accomplished by adding an error term to the conditional mean μ, so that the variance will be greater than the mean (Greene, 2003) as:

$$\ln \mu_i = x_i^{'} \beta + \varepsilon_i = \ln \lambda_i + \ln u_i, \quad (u_i = \varepsilon_i) \qquad [3]$$

where ε_i a random error or unobserved variables that is typically assumed in classical regression model, that is, error is assumed to be uncorrelated with x. The conditional distribution remains Poisson-like in the sense that the distribution of y_i conditioned on x_i and u_i with conditional mean (λ_i) and variance (μ_i):

$$f(y_i \mid x_i, u_i) = \frac{e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i}}{y!} \quad [4]$$

Equation 4, is a Poisson variable with mean (λ_i) and error term ($u_i = exp(\varepsilon_i)$) assumed to follow a Gamma distribution. The Poisson-Gamma mixture model is assumed to have a mean of 1.0 (Hilbe & Greene, 2007). The main idea of Poisson-Gamma mixture is to allow for the variance to be greater than the mean by adding an error to the mean ($\lambda_i u_i$) or to technically account for overdispersion inherent in count data. This means that the unconditional distribution of $f(y_i \mid x_i, u_i)$ can be derived by integrating u_i out of the density (Greene, 2003; Hilbe & Greene, 2007):

$$f(y_i \mid x_i) = \int_0^\infty \frac{e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i}}{y!} g(u_i)du_i \quad [5]$$

The error term, u_i, defines the choice of distribution and takes the gamma type error distribution. The $g(u_i)$ from equation 5, is a two-parameter gamma distribution (Greene, 2003), written out as:

$$g(u_i) = \frac{\theta^\theta}{\Gamma(\theta)} \exp(-\theta u_i) u_i^{\theta-1} \quad [6]$$

where Γ(.) is a gamma function. The unconditional distribution for y_i (Greene, 2003) can be written as:

$$f(y_i \mid x_i) = \int_0^\infty \frac{\exp(-\lambda_i u_i)(\lambda_i u_i)^{y_i}}{\Gamma(y_i+1)} \frac{\theta^\theta}{\Gamma(\theta)} \exp(-\theta u_i) u_i^{\theta-1} du_i, \quad y_i = 0,1,... \quad [7]$$

where the y factorial, y! = $\Gamma(y_i + 1)$. From equation 6, the mean of gamma distribution is ɵ/θ and variance ɵ/θ^2. Constraining the mean to one implies setting ɵ = θ, which results in one parameter gamma variance, where ɵ/θ^2=1/θ. This expression explains why the variance is a quadratic function of the mean. The term 1/θ is the overdispersion parameter of Negative binomial. The smaller the value of θ the higher the overdispersion allowing the mean and variance to be different, unlike the Poisson model. The negative binomial presents a more realistic model for estimating and understanding missed assessments by students. Missed assessments by students are by nature events that are positively correlated by the frequency occurrences which in turn induces larger variance. Applying properties of gamma's integral (Greene, 2003) in equation 7, yields:

$$f(y_i \mid x_i) = \frac{\theta^\theta \lambda_i^{y_i} \Gamma(\theta + y_i)}{\Gamma(y_i+1)\Gamma(\theta)(\lambda_i+\theta)^{\theta+y_i}} \quad [8]$$

Using the same properties of gamma function, Hilbe & Greene (2007) provided a convenient version of equation 8, as:

$$f(y_i \mid x_i) = \frac{\Gamma(y_i+\theta)}{\Gamma(y_i+1)\Gamma(\theta)} \left(\frac{\theta}{\lambda_i+\theta}\right)^\theta \left(\frac{\lambda_i}{\lambda_i+\theta}\right)^{y_i}, \quad y_i = 0,1,... \quad [9]$$

Dividing equation 9 through by θ yields:

$$f(y_i \mid x_i) = \frac{\Gamma(y_i + \theta)}{\Gamma(y_i + 1)\Gamma(\theta)} \left(\frac{1}{1 + (\lambda_i / \theta)} \right)^{\theta} \left(1 - \frac{1}{1 + (\lambda_i / \theta)} \right)^{y_i}, \quad y_i = 0,1,... \tag{10}$$

Redefining the dispersion parameter obtained above as $\alpha = 1/\theta$, and plugging it back to equation 10, yields a density that is commonly recognized in the literature (Cameron & Trivedi,1999; Hilbe & Greene, 2007):

$$f(y_i \mid x_i) = \frac{\Gamma(y_i + 1/\alpha)}{\Gamma(y_i + 1)\Gamma(1/\alpha)} \left(\frac{1}{1 + \alpha\lambda_i} \right)^{1/\alpha} \left(\frac{\alpha\lambda_i}{1 + \alpha\lambda_i} \right)^{y_i}, \quad y_i = 0,1,... \tag{11}$$

Empirical Specification of Model

To examine the effect of internet connectivity and other students' characteristics on missed assessments, we adopt equation 12, for estimation. Estimation of the NB model parameters (β,α) is very straight forward using software packages such as, Stata, SAS, etc. The likelihood function can be set up from equation 11, as:

$$\lambda = \exp(x_i'\beta)$$

$$L(\beta, y_i, \alpha) = \sum_{i=1}^{n} \left\{ y_i \ln\left(\frac{\alpha \exp(x_i'\beta)}{1 + \alpha \exp(x_i'\beta)} \right) - \left(\frac{1}{\alpha} \right) \ln(1 + \alpha \exp(x_i'\beta) + \ln\Gamma\left(y_i + \frac{1}{\alpha} \right) - \ln\Gamma(y_i + 1) - \ln\Gamma\left(\frac{1}{\alpha} \right) \right\}$$

[12]

Differentiating equation 12, with respect to coefficients and equating to zero yields likelihood equations as follows:

$$\frac{\partial \log L}{\partial \beta} = \sum_{i=1}^{N} \left(\frac{y_i - \exp(x_i'\beta)}{1 + \alpha \exp(x_i'\beta)} \right) x_i = 0 \tag{13}$$

The likelihood equation of Poisson is similar to NB equation 13, but the estimates differ due to the denominator term. However, as the parameter (α) gets closer to zero, the NB approaches Poisson model and provides the best possible explanation why the NB is regarded as a special form of Poisson (Hilbe & Greene, 2007).