Research Article

Read Article history for more information

Inverted U-shape Trajectories of Student Engagement and Teacher Satisfaction in Online Classes: Nonlinear Impact of Zoom Fatigue

Nikhil Patel

Department Of Computer Science, Mumbai University, India

patelnikhilr88@gmail.com

Sandeep Trivedi

IEEE Member, Graduated from Technocrats Institute of Technology India,
sandeep.trived.ieee@gmail.com

Article history:
Received: 2021/02/18
Available online: 2021/08/26

Abstract

Long class periods are physically and intellectually exhausting for both students and instructors in the physical world. When that practice is applied to the digital world, things become much more difficult. When instructors teach online, many teachers discover that their synchronous Zoom lessons go on for far longer than expected. Participating in such lengthy video calls may be stressful for instructors and students. Video calls often demand more attention than in-person talks do because users have a much more restricted view of non-verbal cues, such as body movements. This makes it more difficult to absorb the information being sent. This research purposes the hypothesis of inverted U-shape trajectories in online classes. It is postulated that there is an ideal length of online classes. The purpose of this study is to determine whether or not this hypothesis is correct and to determine the length of an online class of material posting that is ideal for use on social media platforms. The implementation of many quadratic longitudinal models has taken place. The dataset includes the length and student engagement scores and teacher satisfaction. Data are on a weekly basis for five different schools, totaling 525 samples of longitudinal datasets. These data confirm our hypothesis that increasing the duration of an online class increases student engagement and instructor satisfaction up to a certain length. However, both students' engagement and instructors' satisfaction suffer if online class sessions are made longer.

Keywords: Inverted U-shape, Longitudinal models, Student Engagement, Teacher satisfaction, Zoom fatigue

Declarations

Competing interests:

The author declares no competing interests.

1. Introduction

Various things have shifted and developed since early 2020, when Covid-19 first appeared on the scene of the world's stage. Virtual contacts between people are now the norm in order to reduce the likelihood of the coronavirus being transmitted from one person to another. Video conference calls have taken the place of in-person meetings, courses, and webinars as the primary means by which we participate in social interactions. Even get-togethers with the family are now often conducted while seated in front of computers. When things started to go back to normal, the hopeful perspective was that teleconference would become obsolete for the most part. However, they have not become so. Ten months after the epidemic first appeared, many teachers are still teaching and interacting with their pupils, parents, and coworkers via the use of video conferencing software. This may be done as part of a hybrid approach or full-time.

All of this time spent staring at screens has resulted in a fast-expanding issue known as Zoom fatigue, dubbed after the widely used video conferencing software Zoom. According to the findings of the studies the cognitive demands placed on participants by video conferencing communication increased (Cranford, 2020; Zaini & Supriyadi, 2021). In addition to having to organize the teleconference, they must also use technology to give the impression that they are making eye contact with one another while at the same time attempting to understand what the other person is saying. When combined, all of these actions have the potential to be psychologically draining (Bailenson, 2021).

A paper in the journal Technology, Mind, and Behavior in 2021 indicated four probable reasons of Zoom fatigue (Bailenson, 2021). More research is required, but these possibilities were presented in the publication. Along with the mental workload that comes with sending and receiving nonverbal signals on camera, other aspects of videoconference that can be exhausting include up-close eye staring, less movement due to the have to be in the camera view, and the impacts of having to look at themselves in the reflection of the webcam (Peper et al., 2021; Shockley et al., 2021).

Because of the unprecedented increase in their usage in reaction to the Covid-19, informal social experiments have been initiated. These experiments are demonstrating at a population size something that has always been true: that engaging in virtual contacts may be quite taxing on the brain (Jiang, 2020) (Geraldine Fauville et al., 2021). Researchers have discovered that participating in video conferences has an effect on a wide variety of cognitive processes. It does this by silencing our mirror neurons, which are what allow us to comprehend and sympathize with the experiences of others, and by confusing the neurons in the global positioning system. In the second scenario, the Zoomer is placed together in one physical area and another, maybe very distant, virtual world. This results in confusion and exhaustion for the Zoomer due to the nature of the virtual engagement (G. Fauville et al., 2021). It could seem a lot like what occurs to mental effort when brain is attempting to find out locations, and it can help explain why one hour on Zoom might feel like several hours in person.

Even when they are not speaking, humans are still able to communicate. During a face-to-face conversation, the brain is partially focused on the words that are being verbalized, but it also emanates extra factor from multitude of non-verbal cues (Tufvesson, 2020). These non-verbal cues include if somebody is approaching you or mildly turned away, whether they are fiddling while you talk, or whether they are quickly inhaling in initiation to interrupt. These hints assist construct a more complete portrait of what has been communicated as well as the reaction that is anticipated from the recipient (the listener) (Rathee, Rathee, et al., 2014; Trivedi & Patel, 2020). As a result of our evolutionary history as social creatures, most of us have an innate ability to pick up on these signals, which requires very little effort on our part to decipher and has the potential to pave the way for emotional connection.

On the other hand, a regular video conference will hamper these entrenched skills and instead demand that one pay persistent and concentrated attention to the words being said. It is impossible to see a person's hand motions or any other kind of body language if the camera is exclusively focused on the upper shoulders and chest area of that individual (Williams, 2021).

A classroom environment makes it easier to pick up on a variety of subtle indicators, such as facial gestures and body language (Murphy & Manzanares, 2008). Teachers place a high importance on being able to watch their students' responses live and being prepared to pick up on these subtle indications (Gillies, 2008).

According to Wiederhold, the notion that most videoconferences simply frame a person's face removes the possibility of receiving a great number of these nonverbal indicators (Wiederhold, 2020b). Furthermore, the speakers on video conversations, whether they be an instructor, student, family, coworker, or administrator, might look disproportionately huge on the screen. According to a number of studies, a significant portion of people find this to be unsettling and even daunting, particularly when the screen is on the more big side (Wiederhold, 2020a) (Pierre et al., 2021).

Wiederhold recommends that instructors make time in their schedules to take those all intervals, even if it's just for a few minutes at a period, in order to relieve the impacts of videoconferencing fatigue. This is the most crucial step, although she also recommends doing few minutes of breathing exercises before and after each session to help reset your baseline. In addition, she suggests setting aside a little portion of the class period for relaxation activities, which are not only good for the students but may also help teachers (Riva et al., 2021).

Even though Zoom is a great tool that has helped tens of thousands, if not millions, of students and instructors communicate with one another via the platform, using it can be time-consuming and stressful (Vandenberg & Magnuson, 2021). Stress is almost unavoidable for students who have been confined for a long time and are required to participate in constant online classes (Samara & Monzon, 2021).

The use of video calling to the point of exhaustion has been evidenced to anticipate higher levels of depression, nervousness, strain, and dissatisfaction with one's life (Mukhopadhyay, 2020). This is the case despite the fact that having digital interactions may be preferable for one's well-being than experiencing no social interactions at all. Students have a number of challenges while engaging in virtual conversation, one of which is the catastrophic decline in academic performance that occurred during the epidemic, particularly among vulnerable young people. This idea also applies to students in higher education: According to the findings of a research that was published in the year 2021 in the journal NeuroRegulation, over 94% of undergraduate students reported having "medium to significant difficulties with digital learning (Peper et al., 2021).

2. Methodology

Proposed Model 1.

To test for the presence of an inverted u-shaped curve, the model includes a duration squared term.

$$(Student\ Engagement)_i = \alpha + \beta_1 Duration_i + \beta_2 Duration_i^2 + \varepsilon_i$$

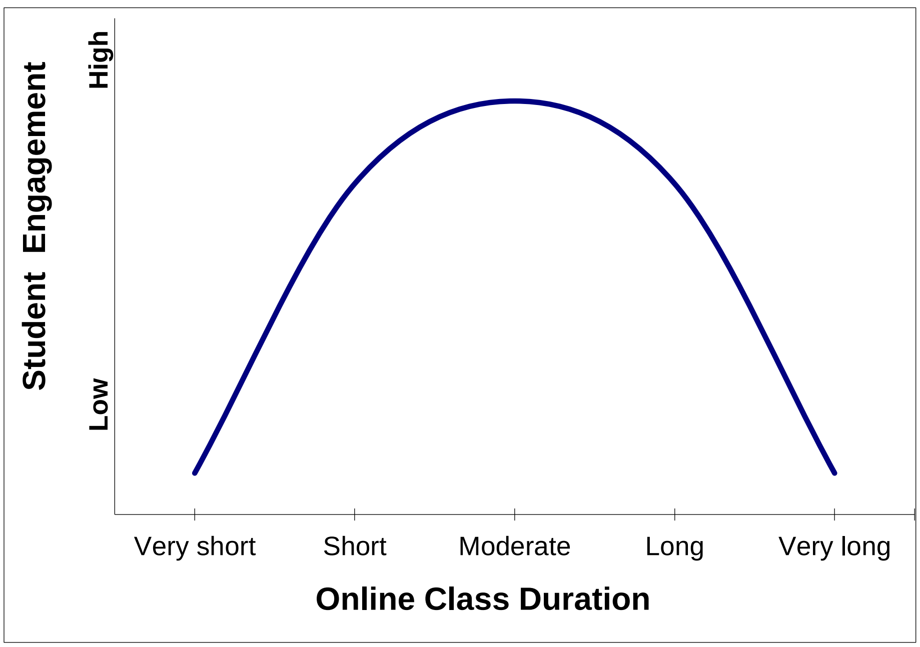

Figure 1. Inverted U-shaped relationship between student learning engagement and online class duration

According to this graph, as duration of online class increases, so does student engagement up to a certain point. Increases in duration of online class diminish student involvement beyond that point.

Proposed Model 2.

$$(Teacher\ Satisfaction)_i = \delta + \gamma_1 Duration + \gamma_2 Durationn_i^2 + \varphi_i$$

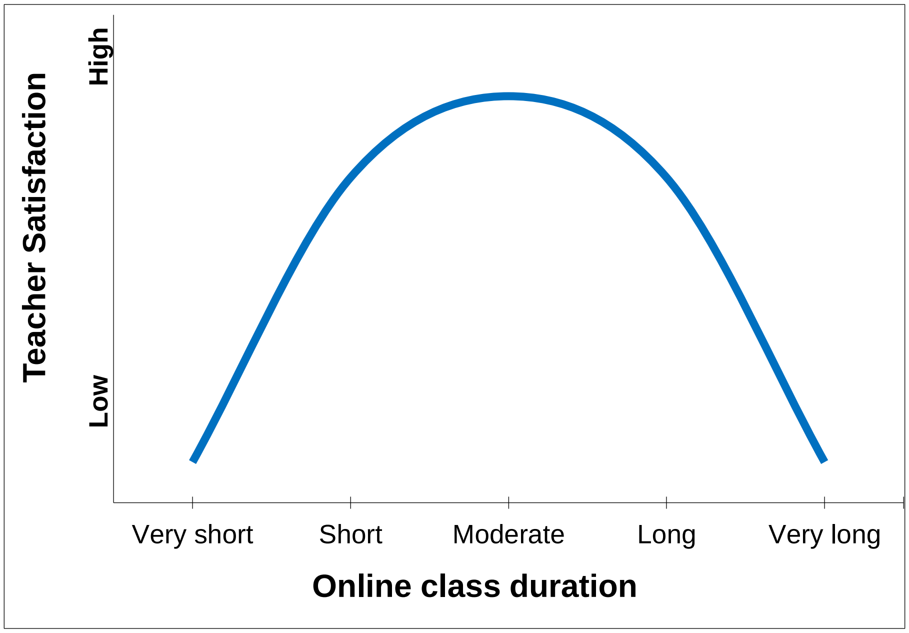

Figure 2. Inverted U-shaped relationship between student engagement and post length of online class

The graph demonstrates that as the duration of online class increases up to a certain level, satisfaction level of a teacher grows. After that, increasing the duration of online class reduces satisfaction level of a teacher.

Longitudinal models

A longitudinal model involves the collection of data for cross sections over an extended period of time (G. Fitzmaurice et al., 2008). Utilizing longitudinal models, often referred to as panel models, is the method of choice in situations when the sampling unit includes collecting recurring data over the course of an extended period of time. Methods need to take into consideration the clustered structure of the data since data points from the similar level of analysis are expected to be closely connected across time (i.e. they indicate the similar unit of analysis) (Bartolucci et al., 2014) (Snijders, 2005). The municipalities included in this study provide annual data, which makes possible an examination of longitudinal data.

There is a great deal of flexibility available when it comes to the analysis of longitudinal datasets (Vermunt et al., 2008). This flexibility is conditional on the assumptions that are made, such as whether or not to utilize random or fixed effects. In the statistical literature, the terms "fixed-effects" and "random-effects" refer to two different types of assumptions that are made on the connections of error factors inside the model (Hedges, 1994).

The following is how the generic model works when considering both random and fixed effects (Penny & Holmes, 2007; Sun et al., 2000):

$$y_{it}= x_{it}\beta + \alpha_i + \varepsilon_{it}$$

In this equation, yit represents the dependent variables for unit I at period t, and xit represents the independent factors with the coefficients for unit I at period t Both I and it it are residual terms, with I referring to stochastic individual impacts (period constant) for unit I and it referring to an idiosyncratic error (period variant) for unit I at period t Both I and it are error terms (Penny & Holmes, 2007).

It is a presumption in random-effect models that at any given instant, I is not linked with any of the predictor variable xit. These models look at data across time. To put it differently, unobserved impacts in the equation are only randomly correlated with the variables that explain the data. This is a significant assumption to adopt, and it will almost likely be invalidated, especially in models with a limited number of variables that may explain the data.

i is permitted to correlate with predictor variables xit in fixed-effect models, which is a less strict assumption than other types of model assumptions (Raudenbush, 2009). This means that unobserved attributes may be connected to explanatory variables. Fixed-effect models are able to take into consideration unobserved attributes that remain constant (or steady) throughout the course of time. As a consequence, these models provide estimates that are independent of any regression coefficient s that may exist between errors and explanatory variables (Strumpf et al., 2017). In addition to analyzing error terms inside and across models, the Hausman specification check may also be used to decide whether fixed or random panel models should be applied to the dataset (Allison, 2009; Hirai & Kaufman, 2017; Raudenbush, 1994).

3. Results

Proposed model 1 results

The tables 1, 2, and 3 describe the findings of the various longitudinal estimating approaches used to model 1. Student engagement is the dependent variable, while duration and duration squared are the independent variables.

The regression coefficient between length of online class and regression coefficient is 0.658. A test to determine the significance of the regression coefficient is also given in the table. A p-value that is less than 0.05 indicates that the t-statistic is greater than or equal to 3.156. Because the p-value is lower than 0.05, the coefficient value of 0.658 is considered to be statistically significant. It seems from this that length of online class does have a large beneficial influence on engagement. The regression coefficient between squared frequency and regression coefficient is -1.0766. The table also includes the results of a significance test for the regression coefficient. The result of the t-statistic is -7.599, and the p-value is more than 0.05. The fact that the p-value is lower than 0.05 indicates that the coefficient value of 1.0766 is statistically significant. This suggests that there is a link between length of online class and engagement that is formed like an inverted letter "u." In tables 2 and 3, one may find outcomes that are practically identical to one another. These findings provide evidence in support of our hypothesis that there is an increase in students engagement when the length of online class is increased to a certain extent. Afterwards, increasing the length of online class will result in a lower engagement rate from the students. In addition to this, we determined the greatest point possible by using the optimization rule. According to the findings, the best length of online class is 25 minutes. This indicates that the engagement level of student will decline if the length of online class is increased to more than 25 minutes.

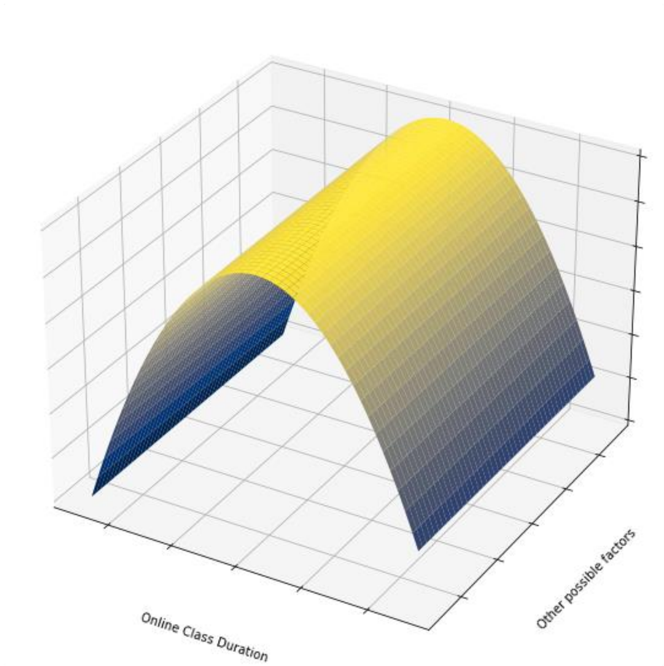

Figure 1. Shows that after a certain length of online class the students engagement starts to decline. (with linear term 0.66, and a negative quadratic term -1.08)

Table 1. Panel Least Squares

Dependent Variable: STUDENT_ENGAGMENT
Method: Panel Least Squares
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	0.658566	0.208671	3.156004	0.0017
DURATION_SQURED	-1.076674	0.141677	-7.599470	0.0000
C	-0.047023	0.269326	-0.174594	0.8615

R-squared	0.113875	Mean dependent var	-1.226765
Adjusted R-squared	0.110480	S.D. dependent var	5.326191
S.E. of regression	5.023365	Akaike info criterion	6.071775
Sum squared resid	13172.25	Schwarz criterion	6.096137
Log likelihood	-1590.841	Hannan-Quinn criter.	6.081315
F-statistic	33.54074	Durbin-Watson stat	1.915590
Prob(F-statistic)	0.000000		

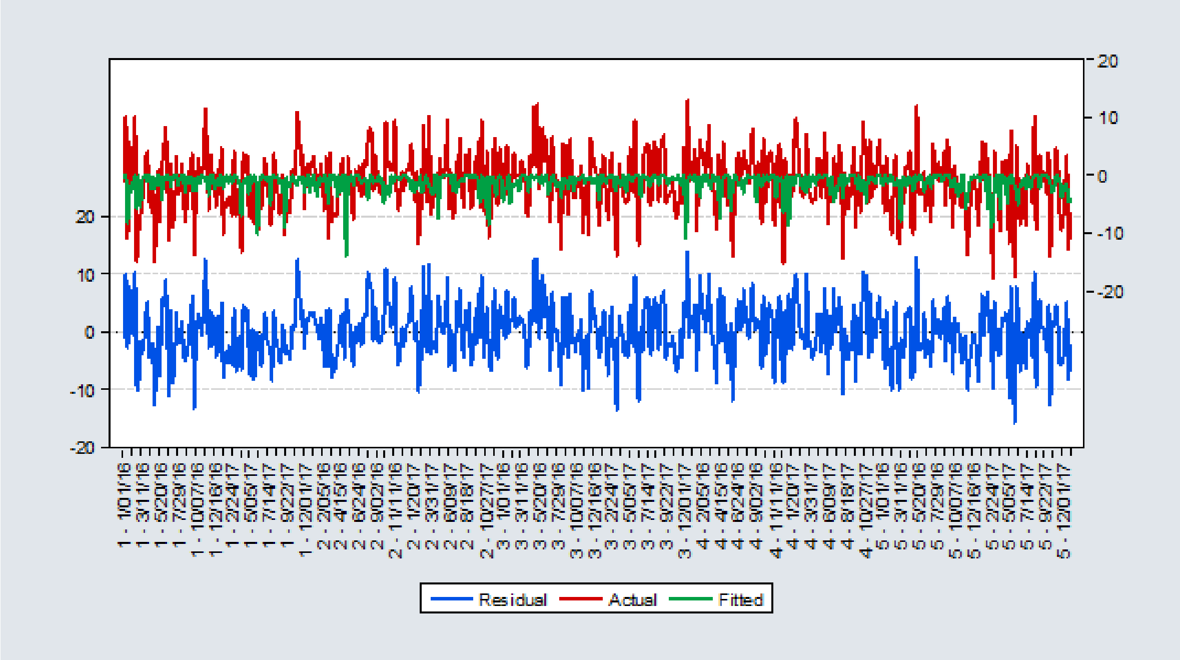

Figure 2. Residual, Actual, and fitted series for proposed model 1.

Table 2. Fixed Effect

Dependent Variable: STUDENT_ENGAGMENT
Method: Panel EGLS (Cross-section weights)
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	0.585377	0.207444	2.821856	0.0050
DURATION_SQURED	-1.051503	0.139898	-7.516240	0.0000
C	-0.073799	0.266620	-0.276795	0.7820

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.129725	Mean dependent var	-1.212718
Adjusted R-squared	0.119644	S.D. dependent var	5.314750
S.E. of regression	4.989957	Sum squared resid	12898.03
F-statistic	12.86901	Durbin-Watson stat	1.954300
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.132248	Mean dependent var	-1.226765
Sum squared resid	12899.13	Durbin-Watson stat	1.956232

Table 3. Method: Panel EGLS (Cross-section random effects)

Dependent Variable: STUDENT_ENGAGMENT
Method: Panel EGLS (Cross-section random effects)
Date: 07/20/22 Time: 01:03
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Swamy and Arora estimator of component variances
Cross-section SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	0.649685	0.208608	3.114376	0.0019
DURATION_SQURED	-1.074937	0.141324	-7.606168	0.0000
C	-0.048817	0.258948	-0.188520	0.8505
Effects Specification				
			S.D.	Rho
Cross-section random			0.223215	0.0020
Idiosyncratic random			4.990064	0.9980
Weighted Statistics				
R-squared	0.113476	Mean dependent var		-1.115195
Adjusted R-squared	0.110079	S.D. dependent var		5.315428
S.E. of regression	5.014341	Sum squared resid		13124.97
F-statistic	33.40830	Durbin-Watson stat		1.922480
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.113871	Mean dependent var		-1.226765
Sum squared resid	13172.30	Durbin-Watson stat		1.915572

Proposed Model 2 results

The findings of a number of different longitudinal estimating procedures are shown in Tables 4, 5, and 6 with respect to Model 2. The teachers' satisfaction level is the dependent variable, while length of online class and length of online class squared are the independent variables.

According to what has been shown in table 4, The coefficient of regression for the length of online class is 0.9533. There is also a significance test for the regression coefficient included in the table. The t-statistic comes in at 4.628, and the p-value for it is lower than 0.05. The coefficient value of 0.9533 is deemed significant since the p-value is lower than 0.05, which is the threshold for significance. This demonstrates that length of online class has a beneficial impact on the proportion of positive emotion in teachers. The coefficient of squared regression on length of online class measures -0.8075. There is also a significance test for the regression coefficient included in the table. The t-statistic is -5.773, and the p-value for the experiment is less than 0.05. The coefficient value of -0.8075 is regarded relevant since the p-value is lower than 0.05, which is the significance threshold. This seems to indicate that there is an upside-down u-shaped link between length of online class and teacher's satisfaction. The data shown in Tables 5 & 6 are almost similar to one another. These data provide evidence in favor of our hypothesis, which states that growing the length of online class up to a certain threshold would result in an increase in the proportion of good sentiments or positive mentions in teachers. Increasing the length of online class after that point will result in decreased satisfaction from the teachers. Both the residual and the fitted graph demonstrate that the estimate does not include any outliers that may cause problems.

In order to determine the peak height, we further used an optimization technique. According to the data, the optimal length of online class of was determined to be 31 minutes. This indicates that the satisfaction level of the instructors will drop if the length of online class become more than half hour.

Table 4. Panel Least Squares

Dependent Variable: TEACHER_SATISFACTION
Method: Panel Least Squares
Date: 07/20/22 Time: 01:07
Sample (adjusted): 1/01/2016 12/29/2017
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	0.953353	0.205989	4.628165	0.0000
DURATION_SQURED	-0.807527	0.139857	-5.773955	0.0000
C	0.733083	0.265865	2.757354	0.0060

R-squared	0.093832	Mean dependent var	-0.145360
Adjusted R-squared	0.090360	S.D. dependent var	5.199272
S.E. of regression	4.958809	Akaike info criterion	6.045906
Sum squared resid	12835.87	Schwarz criterion	6.070269
Log likelihood	-1584.050	Hannan-Quinn criter.	6.055446
F-statistic	27.02594	Durbin-Watson stat	1.923080
Prob(F-statistic)	0.000000		

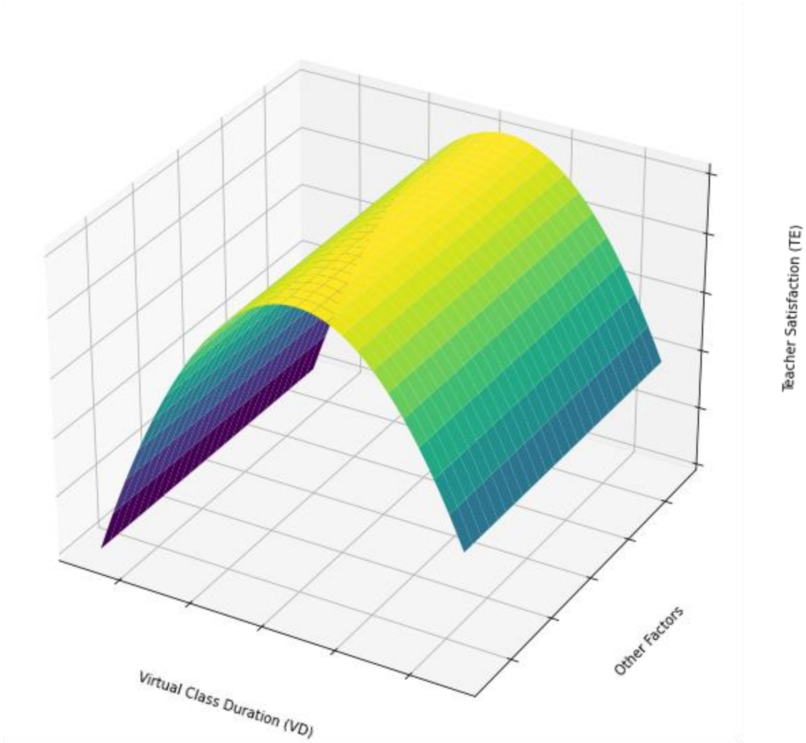

Figure 2. *Shows that after a certain length of online class the satisfaction of teachers starts to decline. (with linear term 0.95, and a negative quadratic term -0.81)*

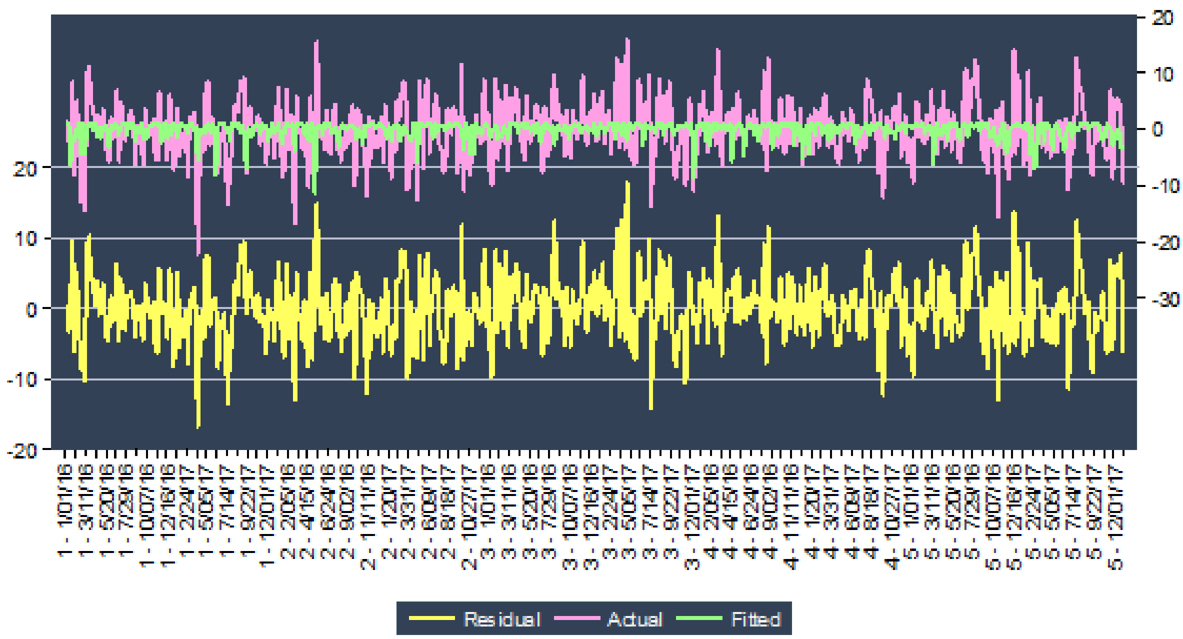

Figure 4. Residual, Actual, and fitted series for proposed model 2.

Table 6. Fixed effect

Dependent Variable: TEACHER_SATISFACTION
Method: Panel EGLS (Cross-section SUR)
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	1.003241	0.194914	5.147105	0.0000
DURATION_SQURED	-0.767472	0.132418	-5.795826	0.0000
C	0.688160	0.246083	2.796459	0.0054

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.111543	Mean dependent var	-0.037097
Adjusted R-squared	0.101252	S.D. dependent var	1.061494
S.E. of regression	1.006543	Sum squared resid	524.8009
F-statistic	10.83886	Durbin-Watson stat	1.959247
Prob(F-statistic)	0.000000		

Table 6. Panel EGLS (Cross-section random effects)

Dependent Variable: TEACHER_SATISFACTION
Method: Panel EGLS (Cross-section random effects)
Periods included: 105
Cross-sections included: 5
Total panel (balanced) observations: 525
Swamy and Arora estimator of component variances
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLASS_DURATION	0.946848	0.214151	4.421403	0.0000
DURATION_SQURED	-0.805079	0.145443	-5.535366	0.0000
C	0.730471	0.294815	2.477722	0.0135

Effects Specification

	S.D.	Rho
Cross-section random	0.306004	0.0038
Idiosyncratic random	4.954817	0.9962

Weighted Statistics

R-squared	0.093127	Mean dependent var	-0.122830
Adjusted R-squared	0.089652	S.D. dependent var	5.190383

S.E. of regression	4.952255	Sum squared resid	12801.96
F-statistic	26.80218	Durbin-Watson stat	1.928275
Prob(F-statistic)	0.000000		
	Unweighted Statistics		
R-squared	0.093829	Mean dependent var	-0.145360
Sum squared resid	12835.90	Durbin-Watson stat	1.923176

4. Conclusion

The use of video conferencing has evolved into the modern way of doing educational tasks. Virtual meetings have, for many people, become the preferred alternative to in-person meetings, which traditionally offered the opportunity to have gatherings in a variety of settings or even engage in moving meetings. After participating the online class with video conferences, students and teachers may get a sensation of exhaustion or burnout that is often described as "Zoom Fatigue." Video conferencing, on the other hand, has a number of clear advantages. For example, it enables people to form social ties during times of loneliness and makes it easier for people with chronic health issues to participate in the workforce or in educational settings. However, the use of this resource may come at a price.

Although there is no established method for diagnosing Zoom fatigue, its symptoms, which include feelings of tiredness or burnout, are claimed to be real. This does not imply that it is unavoidable for anybody who engages in video conferencing that they will get Zoom weariness. The adoption of tools that facilitate video conferencing is expected to continue as we transition to the new normal. Students and teachers may reduce the likelihood of acquiring Zoom fatigue and increase the level of productivity by being more conscious of the impact and causes of the condition.

The mixture of having to pay attention to these indicators shown on a computer screen that is quite small and having a continual reminder that we are being watched might make students and teachers feel uneasy and cause our brains to get exhausted. The instructors have the ability to significantly cut down on the dreaded Zoom weariness by using certain tactics and having a fundamental comprehension of how virtual learning functions. The use of webcam hangouts and virtual meetings is becoming more commonplace in both private households and public businesses. Because this type of social connection may be mentally exhausting, it is essential to reduce stress in order to prevent mental weariness from coming in.

Consequently, teachers' students should utilize the technologies as wisely as possible, ensuring that virtual classes, courses, and discussions are brief and get to the point as soon as reasonably practicable. In addition, we should all make it a point to maintain proper Zoom hygiene by imposing limits on the ways in which we use the technological tools.

Teachers as well as school administrators should avoid extended, lecture-based Zoom calls this school year, according recommendations of this research. If teachers are required to teach students remotely, they should provide them assignments that they can complete while they are not connected to the internet so that they may have individual or small group discussions. Any lengthy virtual class beyond optimal length may be damaging to the student's social, emotional, physical, intellectual, and cognitive development. Brief full-group virtual classes may be utilized for initial discussions and debriefings, but anything longer than that might cause disengagement in students and dissatisfaction in teachers.

References

Allison, P. D. (2009). *Fixed effects regression models*. Sage Publications. https://books.google.at/books?id=3UxaBQAAQBAJ

Bailenson, J. N. (2021). Nonverbal overload: A theoretical argument for the causes of Zoom fatigue. *Technology, Mind, and Behavior*, *2*(1). https://doi.org/10.1037/tmb0000030

Bartolucci, F., Farcomeni, A., & Pennoni, F. (2014). Rejoinder on: Latent Markov models: a review of a general framework for the analysis of longitudinal data with covariates. *Test* , *23*(3), 484–486.

Cranford, S. (2020). Zoom fatigue, hyperfocus, and entropy of thought. *Matter*, *3*(3), 587–589.

Fauville, G., Luo, M., Queiroz, A. C. M., Bailenson, J. N., & Hancock, J. (2021). Zoom Exhaustion & Fatigue Scale. *Computers in Human Behavior Reports*, *4*, 100119.

Fauville, Geraldine, Luo, M., Muller Queiroz, A. C., Bailenson, J. N., & Hancock, J. (2021). Nonverbal Mechanisms Predict Zoom Fatigue and Explain Why Women Experience Higher Levels than Men. In *Available at SSRN*. https://doi.org/10.2139/ssrn.3820035

Fitzmaurice, G., Davidian, M., Verbeke, G., & Molenberghs, G. (2008). *Longitudinal Data Analysis* (Garrett Fitzmaurice, M. Davidian, G. Verbeke, & G. Molenberghs, Eds.). Chapman & Hall/CRC. https://doi.org/10.1201/9781420011579

Gillies, D. (2008). Student perspectives on videoconferencing in teacher education at a distance. *Distance Education*, *29*(1), 107–118.

Hedges, L. V. (1994). Fixed effects models. *The Handbook of Research Synthesis*, *285*. https://books.google.com/books?hl=en&lr=&id=p-aFAwAAQBAJ&oi=fnd&pg=PA285&dq=%22fixed-effects%22+and+%22random-effects%22++&ots=TWzRRlcLVI&sig=xNadn1ffFzRFnUl1DVv1GrtPrik

Hirai, A. S., & Kaufman, J. S. (2017). Fixed versus random effects models for multilevel and longitudinal data. *Methods in Social Epidemiology. San Francisco: Jossey-Bass*.

Jiang. (2020). The reason Zoom calls drain your energy. *BBC Worklife*. https://www.counsellingresources.co.nz/uploads/3/9/8/5/3985535/the_reason_zoom_calls_drain_your_energy.pdf

Mukhopadhyay. (2020). COVID-19 and ’zoom’for remote teaching: Enhancing student engagement. *The Sentinel, Post*. https://www.researchgate.net/profile/Boidurjo-Rick-Mukhopadhyay/publication/340503926_Using_Zoom_to_Enhance_Student_Engagement_in_a_Virtual_Classroom/links/5eb13489299bf18b9595bb57/Using-Zoom-to-Enhance-Student-Engagement-in-a-Virtual-Classroom.pdf

Murphy, E., & Manzanares, M. A. R. (2008). Contradictions between the virtual and physical high school classroom: A third-generation Activity Theory perspective. *British Journal* *of Educational Technology: Journal of the Council for Educational Technology*, *39*(6), 1061–1072.

Patel, N., & Trivedi, S. (2020). Choosing Optimal Locations for Temporary Health Care Facilities During Health Crisis Using Binary Integer Programming. *Sage Science Review of Applied Machine Learning*, *3*(2), 1–20.

Penny, W., & Holmes, A. (2007). Random effects analysis. *Mapping: The Analysis of Functional Brain …*. https://books.google.com/books?hl=en&lr=&id=G_qdEsDlkp0C&oi=fnd&pg=PA156&dq=%22fixed-effects%22+and+%22random-effects%22++&ots=Xn1ODCQ8XH&sig=joqyekY1XmUmrLlfEQV25lpDlTE

Peper, E., Wilson, V., Martin, M., Rosegard, E., & Harvey, R. (2021). Avoid zoom fatigue, be present and learn. *NeuroRegulation*, *8*(1), 47–56.

Pierre, Y., Rathee, N. K., & Rathee, V. S. (2021). Developing cross-cultural competency through multicultural perspective: An exploratory inquiry. *European Scientific Journal*, *17*(27). https://doi.org/10.19044/esj.2021.v17n27p324

Rathee, N. K., Rathee, V. S., & Bhardwaj, S. (2014). Concentration, Reactive-Proactive Aggression, Non-verbal Aggression, and Wellness among Video Games Playing Adolescents. *International Journal Of Science In Society*, *5*(1).

Raudenbush. (2009). Analyzing effect sizes: Random-effects models. *The Handbook of Research Synthesis And*.

Raudenbush, S. W. (1994). Random effects models. *The Handbook of Research Synthesis*, *421*(3.6).

Riva, G., Wiederhold, B. K., & Mantovani, F. (2021). Surviving COVID-19: The Neuroscience of Smart Working and Distance Learning. *Cyberpsychology, Behavior and Social Networking*, *24*(2), 79–85.

Samara, O., & Monzon, A. (2021). Zoom Burnout Amidst a Pandemic: Perspective from a Medical Student and Learner. *Therapeutic Advances in Infectious Disease*, *8*, 20499361211026716.

Shockley, K. M., Gabriel, A. S., Robertson, D., Rosen, C. C., Chawla, N., Ganster, M. L., & Ezerins, M. E. (2021). The fatiguing effects of camera use in virtual meetings: A within-person field experiment. *The Journal of Applied Psychology*, *106*(8), 1137–1155.

Sidky, H., Colón, Y. J., Helfferich, J., Sikora, B. J., Bezik, C., Chu, W., Giberti, F., Guo, A. Z., Jiang, X., Lequieu, J., Li, J., Moller, J., Quevillon, M. J., Rahimi, M., Ramezani-Dakhel, H., Rathee, V. S., Reid, D. R., Sevgen, E., Thapar, V., … de Pablo, J. J. (2018). SSAGES: Software Suite for Advanced General Ensemble Simulations. *The Journal of Chemical Physics*, *148*(4), 044104.

Snijders. (2005). Models for longitudinal network data. *Models and Methods in Social Network Analysis*. https://books.google.com/books?hl=en&lr=&id=4Ty5xP_KcpAC&oi=fnd&pg=PA215&dq=longitudinal+models+&ots=9OIOzgtaK3&sig=a95I5Zmozqskh-5VyCZe_uqcVYY

Strumpf, E. C., Harper, S., Kaufman, J. S., & Oakes, M. (2017). Fixed effects and difference in differences. *Methods in Social Epidemiology*, *1*. https://books.google.com/books?hl=en&lr=&id=_WIWDgAAQBAJ&oi=fnd&pg=PA341&dq=%22fixed-effects%22+and+%22random-effects%22++&ots=s_A8nUiC1P&sig=sm7FmzCt1PRALnqKKrQcnLmguRM

Sun, D., Speckman, P. L., & Tsutakawa, R. K. (2000). Random effects in generalized linear mixed models (GLMMs). *BIOSTATISTICS-BASEL-*, *5*, 23–40.

Trivedi, S., & Patel, N. (2020). Clustering Students Based on Virtual Learning Engagement, Digital Skills, and E-learning Infrastructure: Applications of K-means, DBSCAN, Hierarchical, and Affinity Propagation Clustering. *Sage Science Review of Educational Technology*, *3*(1), 1–13.

Tufvesson. (2020). Zoom fatigue: Why video calls sap your energy. *LSJ: Law Society of NSW Journal*. https://doi.org/10.3316/informit.296655554028254

Vandenberg, S., & Magnuson, M. (2021). A comparison of student and faculty attitudes on the use of Zoom, a video conferencing platform: A mixed-methods study. *Nurse Education in Practice*, *54*, 103138.

Vermunt, Tran, & Magidson. (2008). Latent class models in longitudinal research. *Handbook of Longitudinal*. https://books.google.com/books?hl=en&lr=&id=K2yTbPjYBdQC&oi=fnd&pg=PA373&dq=longitudinal+models+&ots=zri47exqHY&sig=ZDBLprl_KuqPhpV5Gu07z8iiVXA

Wiederhold, B. K. (2020a). Connecting Through Technology During the Coronavirus Disease 2019 Pandemic: Avoiding “Zoom Fatigue.” *Cyberpsychology, Behavior and Social Networking*, *23*(7), 437–438.

Wiederhold, B. K. (2020b). Beyond Zoom: The New Reality. *Cyberpsychology, Behavior and Social Networking*, *23*(12), 809–810.

Williams. (2021). Working through COVID-19:’Zoom’gloom and ’Zoom’fatigue. *Occupational Medicine*. https://academic.oup.com/occmed/article-abstract/71/3/164/6218762

Zaini, M., & Supriyadi, S. (2021). Zoom in Fatigue pada Mahasiswa Keperawatan selama Periode Pandemic Covid-19. *JI-KES (Jurnal Ilmu Kesehatan)*, *5*(1), 64–70.