Understanding cyberslacking intention during Covid-19 online classes: An fsQCA analysis

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Abstract

Due to the Covid-19 pandemic, students have been restricted to their homes and forced to take online classes as an alternative to in-person classes. However, data shows that this enforced online education is resulting in a learning deficit for a generation of students and that many engage in cyberslacking behavior, which is the use of non-work-related internet use during designated work time. The cyberslacking tendency among university students in particular is on the rise. This study employed a fuzzy-set qualitative comparative analysis (fsQCA) along with sentiment analysis using Natural Language Processing (NLP). Findings show five core factors that underpin cyberslacking attention. Alternative paths have been identified based on gender and the students' current education status. The study findings contain a number of contributions, illustrating the different topology of student intention towards cyberslacking and identifying causal factors that influence cyberslacking intention, as well as illustrating student sentiment regarding this behavior.

1. Introduction

Cyberslacking or cyberloafing is defined as the use of IT and the internet for non-business or non-educational purposes during work or study hours [1]. According to Vitak, Crouse and LaRose [2], cyberslacking is a routine deviant behavior in the workplace that has the potential to threaten work productivity and security. Although in the beginning cyberslacking was only studied in terms of business and management literature, the advancements of IT into every sphere of human life has made it a ubiquitous problem especially in the academic arena. From the academic perspective, cyberslacking is defined as student behavior or tendency to use the internet for personal purposes unrelated to class during class time [3].

Traditional learning paradigms are constantly evolving due to constant technological advancements. The recent advancement of COVID-19 has severely affected academia and pushed educational institutions to fully or partially operate in e-learning environments. A massive change in student learning behavior has been seen with this paradigm shift [4, 5]. Students are prone to developing mental health problems because of doing a lot of activities in online classes. These mental health problems, along with student internet habits and social media multitasking, raises the intention of cyberslacking [1]. According to Flanigan and Kiewra [6], 70 to 90 percent of university students in the USA regularly cyberslack during class time by browsing social media or sending texts. Use of such technology for non-academic purposes leads to a decrease in focus span and productivity of the students. Therefore, further analysis is needed to identify the reasons behind the intention to cyberslack among students during online classes.

Though cyberslacking is unpredictable, it is not fully understood what influences the cyberslacking behaviour among students during the pandemic. Research so far has explained how internet surfing and the use of social media causes cyberslacking in the pre-pandemic phase. In that vein, research has emphasized cyberslacking literature by adopting several methodologies such as path analysis [7], confirmatory factor analyses [8], regression models [9], and so on. Previous studies also show that internet habit strength is a main antecedent to explain student cyberslacking behavior. However, due to a sudden shift to online platforms for academic purposes, student cyberslacking behavior is likely to increase. This increase in cyberslacking behavior during the pandemic might also occur due to the presence of mental health problems and adopting new practices. Therefore, these factors are critical for increasing student cyberslacking behavior and should be studied together to assess their effects on student intention toward cyberslacking during online classes.

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Literature indicates that cyberslacking is influenced by strong internet habits, media-multitasking, ethical considerations, and self-regulated learning [2], but no research has examined whether and to what degree internet habit strength, boredom, technostress, media multitasking efficacy, and mental health problems may influence cyberslacking behavior among university students [10]. Therefore, to the best of our knowledge, this study is the first to answer what conditions of technostress, media multitasking efficacy, boredom, mental health problems, and internet habit strength are sufficient to create the causal recipe that explains high intention towards cyberslacking among university students amid the pandemic. To do so, it draws on the established frameworks of social cognitive theory (SCT), the theory of planned behavior, and the social learning theory for guiding the examinations, which is something that has not been present in earlier studies on this issue [2].

Fuzzy-set qualitative comparative analysis (fsQCA) is one of the few first tools for examining causal relationships [11], providing multiple solutions that can explain the same outcome, thus showing how cyberslacking intention among university students is explained by its antecedents. fsQCA offers a deeper insight into the data and should be considered as an alternative and complementary method to traditional variance-based approaches [12]. The findings of fsQCA offer multiple, distinct, and equally effective combinations of internet habit strength, technostress, media multitasking efficacy, boredom, and mental health problems, which explain high intention toward cyberslacking.

The contribution of this paper in the literature is threefold. First, we extend the literature by exploring different topologies of student intention toward cyberslacking through the lens of internet habit strength, technostress, media multitasking efficacy, boredom, and mental health problems as we examine their combined effects on intention toward cyberslacking. Second, we use fsQCA for the first time to present the causal relationship between student intention toward cyberslacking. Finally, sentiment analysis is performed to examine how students from different cultural backgrounds feel about cyberslacking. The findings of this study show that none of the research constructs is either necessary or sufficient for explaining intention toward cyberslacking, instead their combinations lead to cyberslacking. Identifying the interplay among the aforementioned research constructs will help faculty members and practitioners to identify patterns that stimulate student intentions and help them create better academic contents and offer help to fight psychological problems related to mental health and technostress.

The remainder of this paper is organized as follows. The theoretical background on cyberslacking, internet habit strength, technostress, media multitasking efficacy, boredom, and mental health problems is presented in Section 2 along with a discussion on the conceptual model and research hypotheses. Section 3 provides a detailed explanation of the research methodology along with the use of fsQCA and how it is implemented. Section 4 and 5 presents the results from the configurational analysis and the discussions highlighting key facts. Finally, Section 6 discusses the conclusion and implications along with limitations and avenues for future research.

2. Background and Hypotheses Development

It is a known fact that cyberslacking adversely affects productivity in all educational settings [13] and has a high negative impact on the e-learning environment as it causes distraction and affects the student's ability to focus, as discussed in the theory of planned behavior and in the social learning theory. Currently, the entire academia is experiencing a downturn due to the COVID-19 outbreak. Universities are compelling students to adapt to the e-learning environment until the university starts conducting face-to-face classes again. All these sudden and abrupt shifts in academia is causing technostress and mental health problems among university students. Therefore, we further investigate the reasons behind cyberslacking behaviour among the students:

2.1. Technostress and cyberslacking

The term "technostress" was first coined by Bord [14] who defined it as "a modern disease of adaptation caused by the inability of a person to cope with the new technologies healthily." Since then many researchers have tried to define technostress in the context of diverse literature. For instance, in the context of academia, Çoklar and Sahin [15] defined technostress as the difficulty experienced by both teachers and students caused by using information technologies. From the perspective of COVID-19, technostress among students can be defined as the incongruence or misfit between students and e-learning technologies. During the ongoing pandemic, educational institutions worldwide adapted e-learning techniques to help students continue their regular education. Students were compelled to adapt to the new normal and

spend a vast amount of time using ICT and as a result, many students became victims of technostress. Güğerçin [16] in his recent paper showed that high levels of technostress can lead to a higher intention towards cyberslacking. In support of this cyberslacking hypothesis, Kolikant [17] referred to the present generation of students as 'digital natives' since they possess technological fluency and e-adaptability. Hence, the following hypothesis is proposed to understand the relationship between technostress and cyberslacking among university students during the pandemic:
H1: *High technostress among university students leads to cyberslacking.*

2.2. Internet habit strength and cyberslacking

Internet habit strength can be defined as the strength of a person's habit to connect to the internet [18]. This habit is developed from a series of repeated practices which in this case is the behavior to connect to the internet. According to Ding, del Pozo Cruz, Green and Bauman [19], the internet habit will grow stronger during the pandemic since people will get more involved in social media and online websites. Existing studies show that internet habit strength causes negative impacts on people's daily lives and wellbeing [20]. From the academic perspective, due to establishing e-learning environments by the universities, student internet habits will rise during the pandemic phase. This rising internet habit strength among university students will evoke them to show cyberslacking behavior. Therefore, we hypothesize that:
H2: *High internet habit strength among university students leads to cyberslacking.*

2.3. Boredom and cyberslacking

Boredom can be defined as the extent to which a person experiences a negative affective state of under-stimulation and disengagement from his/her situation. According to Mercado, Giordano and Dilchert [21], boredom is an important research construct that is positively related to cyberslacking behavior. Yılmaz and Yurdugül [22] in their study showed that cyberslacking helps prevent students from being "bored." In fact, Finkielsztein [23] reported that students were bored about 50 to 60 percent of the time while listening to lecturers and they tend to show cyberslacking behavior as a coping mechanism. Thus, to combat boredom in online classes, the university students often resort to using IT or depict cyberslacking. As a result, we hypothesize:
H3: *High levels of boredom among university students lead to cyberslacking.*

2.4. Media multitasking efficacy and cyberslacking

Media multitasking efficacy (MME) draws on the social cognitive theory given by Bandura [24]. It refers to the conviction of an individual who is able to use more than one social media simultaneously. A student who has both the skills and ability to engage in multitasking using technology will tend to multitask in social media during online classes. According to Simanjuntak, Nawangsari and Ardi [25], students as "digital natives" perceive the fact that their existing technical skills allow them to access the internet while simultaneously doing online classes. This self-perception is not always true since students tend to overestimate their own capacity and show over-confidence which might lead to cyberslacking. In order to form effective teaching strategies for online learning, teachers should consider effects of student's over-confidence. However, not many pieces of research directly connect media multi-tasking efficacy with cyberslacking behavior in online classes during this COVID-19 crisis. Therefore, this research ties the influence of media multitasking efficacy as a probable cause for increasing cyberslacking behavior, thus proposing the following hypothesis:
H4: *High media multitasking efficacy among university students leads to cyberslacking.*

2.5. Mental health and cyberslacking

University students encounter a pool of challenges leading to mental health problems in the wake of the COVID-19 outbreak. The majority of universities worldwide decided to suspend in-person classes and evacuate the students from halls in response to the escalating concerns surrounding the pandemic. This action can lead to negative psychological consequences among university students [26]. As a result, university students are now experiencing mental health problems (substance use disorders, anxiety, stress, depression, etc.) caused by the abrupt disruption of the semester in addition to the uncertainty whether they will lag behind the others in their careers. Wang, Hegde, Son, Keller, Smith and Sasangohar [27]in their study findings showed that around 70 percent of the students reported that their stress/anxiety levels had increased during the pandemic due to mental health problems. Although researchers are focusing on the antecedents of mental health problems among students amid the pandemic, there is no strong evidence on linking mental health problems with cyberslacking in literature. Thus, to identify whether mental health problems amid the pandemic increases cyberslacking behavior among university students, we hypothesize:

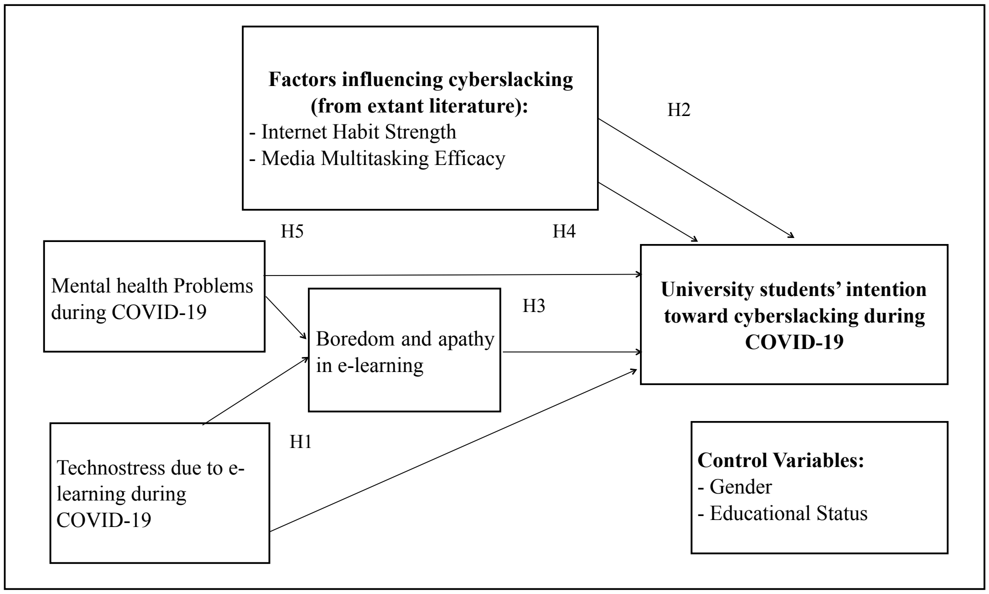

Figure 1. Conceptual model explaining the intention towards cyberslacking among university students.

H5: *Higher levels of mental health problems among university students lead to cyberslacking.*

3. Methodology

Since it is impossible to conduct a field survey due to strict lockdown, this study employs a survey conducted online by collecting individual structured questionnaire responses using a snowball sampling technique. The survey was conducted in Fall 2020. The respondents were mostly students (undergraduates and graduates) from the science division of public universities in Bangladesh since they faced financial problems to bear the cost of internet connection and resources required to attend online classes. The participants were also asked to answer the survey questions based on self-evaluations and to state their views and suggestions on cyberslacking and the ways to minimize it. Participants who were in school or in high school were removed from the sample as this study only focuses on university students. The questionnaire consisted of questions using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). We aimed for about 200 responses, out of which 121 responded. Of the 121 questionnaires, 2 were discarded, resulting in a final sample of 119 university students (98.36 percent of the initial sample). The final sample consisted of 51.67 percent male students and 48.33 percent female students. 32.2 percent of the students were from international backgrounds coming from countries like the United States, India and South Africa. Finally, the sample is diverse regarding the education status as it consists of 71.67 percent who were enrolled in BSc programs, 17.5 percent who were enrolled in MSc programs, and 10.83 percent who were enrolled in a PhD program.

Next, two steps were followed in order to evaluate the research constructs for reliability and internal consistency: The Cronbach's alpha result shows that there is support for construct reliability as all the values are higher than 0.7, so it is evident that the instrument used for the data collection instrument is a good fit for continuing fsQCA. Next, the Stata software was used to perform a correlation analysis with the results showing that there is a limited relationship between the constructs (all variables are within the cut-off threshold of <0.6). The variance inflation factor (VIF) was also run for every variable with the results showing that the VIF for every variable is below 3, which portrays that multi-collinearity is not an issue [28]. This provides sufficient support for the research model proposed.

4. Analysis

This study applies the fuzzy-set Qualitative Comparative Analysis (fsQCA), which is known for integrating the fuzzy sets with the QCA [11]. The advantages of fsQCA occur due to the limitations of existing regression-based methodologies [29]. It keeps the number of causal conditions 'minimum' without omitting variable biases like regression models. In addition to engaging in additional qualitative

Table 1. Descriptive statistics and correlations of research constructs

Variables	**Mean**	**SD**	α	(1)	(2)	(3)	(4)	(5)	(6)
(1) Cyberslacking	3.233333	1.179185	0.7848	1.00					
(2) Internet	3.183333	1.302766	0.7911	0.54*	1.00				
(3) Mental	3.666667	1.33683	0.7850	0.32*	0.26*	1.00			
(4) Multitasking	3.50	1.209208	0.7687	0.46*	0.48*	0.43*	1.00		
(5) Boredom	4.066667	1.275057	0.7721	0.45*	0.43*	0.44*	0.57*	1.00	
(6) Technostress	3.358333	1.24209	0.7962	0.30*	0.27*	0.62*	0.36*	0.36*	1.00

exploration, fsQCA also uses both qualitative and quantitative assessments that create a bridge between qualitative and quantitative methods.

According to Pappas, Mikalef, Giannakos and Kourouthanassis [12], the fsQCA mainly offers two types of configurations. These are created using both the necessary and sufficient conditions in order to provide a number of solutions explaining the same outcome depending on the presence, absence, or on a do not care condition (i.e., either present or absent) of the configurations. The necessary and sufficient conditions are important since it helps differentiate between the core and peripheral conditions. The core ones are the strong conditions needed for the outcome and the peripheral ones are the weak conditions needed for the outcome.

In order to identify if any of the causal conditions is a necessary condition for the presence of intention towards cyberslacking, an analysis of necessity is performed for both the presence and absence of the condition. According to Ragin [30], from a set-theoretic approach, necessity means that a condition is a "superset of the outcome", which means that for each case in the provided sample, the fuzzy-set membership score of the outcome is smaller than the fuzzy-set membership score of the causal conditions. Also, Schneider and Wagemann [31] stated that in order for a condition to be necessary, the consistency should always exceed the threshold of 0.9. Ragin [30] defined consistency as the degree to which the cases in the sample that share a causal configuration agree in displaying the focal outcome. For conducting the analysis of necessity, the dedicated function in fsQCA software 3.0 is used that calculates both the consistency and coverage scores for each and every causal condition as well as their negated values. As all the consistencies lie between 0.39 to 0.74, we can continue our analysis for data calibration.

4.1. Data Calibration

In this step, the variables are required to be calibrated into fuzzy sets by scoring their values from 0 to 1. The 1 denoted full-set membership and the 0 denoted the full non-set membership. There are mainly two methods that researchers apply for data calibration in QCA. The first one is the direct method where the three thresholds need to be defined, which are full membership, full non-membership, and the cross-over point that represent the level that a case belongs to a set [32]. The second one is the indirect method where the measurements require rescaling based on qualitative assessments and the researcher's in-depth knowledge regarding the cases. Although either method can be applied based on the underlying theory and the nature of the cases, for this study we applied the direct method. The three thresholds are based on the 5-point Likert scale from the research questionnaire. Following Rihoux and Ragin [11] recommendations, the calibration process was carried out where 1 denoted the full membership, 0.50 denoted the crossover point, and 0 denoted the full non-membership. Finally, all the values were calibrated on a logistic function to fit into the three thresholds [12].

In this study the calibration process shown below was used in the fsQCA software 3.0 to convert the scale into continuous fuzzy-sets (direct method): Calibrate (x, n1, n2, n3) where x denotes the research construct to be transformed, n1 denotes the full membership range set to 4, n2 denotes the crossover point set to 3, and n3 denotes the full non-membership set to 2. The computational formula for the constructs are given below:

compute: CYB = calibrate (Cyberslacking, 4, 3, 2)
compute: TEC = calibrate (Techno Stress, 4, 3, 2)
compute: IHS = calibrate (Internet Habit Strength, 4, 3, 2)
compute: MME = calibrate (Media Multitasking Efficacy, 4, 3, 2)
compute: BOR = calibrate (Boredom, 4, 3, 2)
compute: MNT = calibrate (Mental Health, 4, 3, 2)

4.2. Generating the truth table

In this step, the fsQCA software 3.0 is used to generate a truth table with the newly computed calibrated data. The truth table generates 2k rows where k equals the number of conditions and each row of

the truth table shows each possible combination for the conditions provided. For example, if there are 3 conditions, the truth table will provide 8 possible logical combinations among them. After generating the truth table we need to sort it by setting the cut-off values of frequency and consistency.
A frequency cut-off point is important to ensure that a minimum number of empirical observations is obtained. For small and medium-sized samples (less than 150 cases), the cut-off point for frequency is 1, but for large-scale samples (more than 150 cases), the cutoff point should be set > 1 [11]. As the number of cases here is 119, the frequency cut-off point is set at "1". Dul [33] also mentioned in his paper that a low consistency threshold might lead to errors, allowing false-positive conditions. Thus, a relatively high consistency threshold is set at >.80, which is a standard metric for fuzzy-set analysis.

5. Findings and Discussion

5.1. fsQCA Analysis

Our fsQCA analysis shows 5 pathways toward cyberslacking behavior among university students. Here, table 2 presents the final outcomes: the smaller black circles (•) represent the presence of a condition, the cross mark (X) its absence, and the blank spaces indicate a "do not care" situation (i.e., the condition may be either present or absent). Large circles (●) symbolize core conditions of the configuration and the small circles (•) symbolize the peripheral ones [34]. The analysis includes set-theoretic consistency values for each of the configurations as well as for the overall solution with all values being above the threshold (>0.8) [12]. The consistency of the configuration measures the degree that a subset relationship has been approximated, and the coverage assesses the empirical relevance of a consistent subset [11].

The overall solution coverage indicates the extent that high intentions can be determined based on the configurations identified and is comparable to the R-square value [12]. An overall solution coverage of 0.651 suggests that the five solutions obtained from the fuzzy analysis cover a substantial proportion of the outcomes. For determining the causal recipe towards cyberslacking behavior, solutions 1-5 present combinations for which the different factors may be present or absent depending on how they combine with each other. The fuzzy membership among groups is identified focusing on natural sets based on demographic information and behavioural traits of the students. These different solution sets help us to find multiple pathways to interpret the reasons behind cyberslacking. They are explained below:

Solution 1: This represents a big portion of the sample where male students belong to both undergraduate and PhD programs. The results show that high mental health problems and low technostress along with the absence of media multitasking efficacy leads to cyberslacking behavior. Despite being a core condition, internet habit strength plays no role. Also, the presence of boredom does not affect the outcome. These findings are intuitive considering the importance of mental health problems and technostress. Additionally, since no girl students are in this solution set, there is more room for research to study the gender and cultural factors behind such results.

Solution 2: This portrays a small part of the sample where both the male and female students belong to MSc programs. From the results, we see that high internet habit strength and low technostress causes increased cyberslacking behavior. On the other hand, the absence of boredom and media multitasking efficacy and no role of mental health problems also lead to a similar outcome. Therefore, from the solutions we can summarize that internet habit strength and technostress should be reduced in order to minimize the intention of cyberslacking.

Solution 3: This represents a small portion of the sample, regardless of the absence of internet habit strength, showing a high intention towards cyberslacking. In terms of gender and education, female students who are doing MSc and male students who are in their undergraduate programs show a high intention towards cyberslacking due to the presence of high mental health problems and low boredom issues. Similarly, the absence of internet habit strength and technostress and no role of media multitasking efficacy are equally responsible for the outcome to occur. These findings show that mental health problems should be dealt with care in order to minimize cyberslacking.

Solution 4: This represents a special group of male students who are pursuing PhDs and female students who are in their undergraduate programs. The solutions depict that high media multitasking efficacy, low internet habit strength, and low boredom leads towards high cyberslacking behavior. The absence of technostress and no role of mental health problems depict that these groups of students are not cyberslacking due to their stress-related problems. As a result, the findings show that students who are less ethical show higher intention toward cyberslacking.

Table 2. Configurations leading to high intention towards cyberslacking

	Solutions				
Configurations	**S1**	**S2**	**S3**	**S4**	**S5**
Internet Habit Strength		●	X	•	●
Techno-stress	•	•	X	X	X
Boredom		X	•	•	X
Media Multitasking Efficacy	X	X		●	
Mental Health Problems	●		●		•
Consistency	0.821293	0.985646	0.865517	0.912037	0.911585
Raw Coverage	0.316715	0.151026	0.184018	0.288856	0.219208
Unique Coverage	0.132698	0.0205278	0.0403226	0.153226	0.090176
Overall Solution Consistency			0.840909		
Overall Solution Coverage			0.651026		

Solution 5: This portrays all the male and female students who are in an undergraduate program. Here the findings show that high internet habit strength, low technostress, and low mental health problems lead to the outcome of a cyberslacking behavior. Also, the absence of boredom and no role of media multitasking efficacy are important. This group of students are highly habituated to using the internet, but they also feel stressed and anxious due to technostress and mental health problems. Their personal lavishness like boredom or media multitasking efficacy does not lead them to cyberslacking. Thus, the results depict that step to be taken to reduce their stress-related problems as well as their habit of internet surfing in order to minimize cyberslacking.

From the solutions discussed above we see that the findings provide support that multiple combinations of sufficient and necessary conditions exist that explain high intention to cyber-slack among university students. The findings of this fsQCA analysis support hypotheses 2, 4, and 5 as high mental health problems, high internet habit strength, and high media multitasking efficacy are important causes for the outcome of cyberslacking. Similarly, the analyses reject hypotheses 1 and 3 as low technostress and low levels of boredom are important for the majority of the solutions. Drawing from the results of fsQCA, we see that technostress intervenes in all paths without being a core condition. Based on the above discussions and the parsimonious solutions, we uncover two topology of university students' intention and their associated pathways to cyberslacking amid the pandemic. These topology are students'psychological intention and habitual intention. Key insights from these topology include:

1.Psychological intention: Students should be given mental support and taught technical skills during this pandemic to reduce cyberslacking. The faculties should provide interactive and interesting contents to reduce cyberslacking.

2.Habitual intention: Awareness among students should be created by showing how cyberslacking hampers their productivity and reduces focus span. Also, internet usage of students should be monitored.

This analysis will further help us to understand the differences among students based on culture, sex and identity. For a better understanding, we run the sentiment analysis and discuss the findings in the next section.

5.2. Applying Sentiment Analysis

Natural Language Processing is one of the popular methodologies that is used to determine the sentiment of users from their extracted opinions [35]. We apply sentiment analysis to identify the key emotional triggers of cyberslacking. Here, the opinions of students collected from the survey were treated as data for sentiment analysis. There was an open-ended survey question focusing on the cultural views of students on their cyberslacking behaviour. Based on the sentiment analysis of the university students on how they view cyberslacking amid the pandemic, the majority of the respondents (71.26 percent) has a positive sentiment. This implies that due to their problems while attending online classes, they are viewing cyberslacking as a

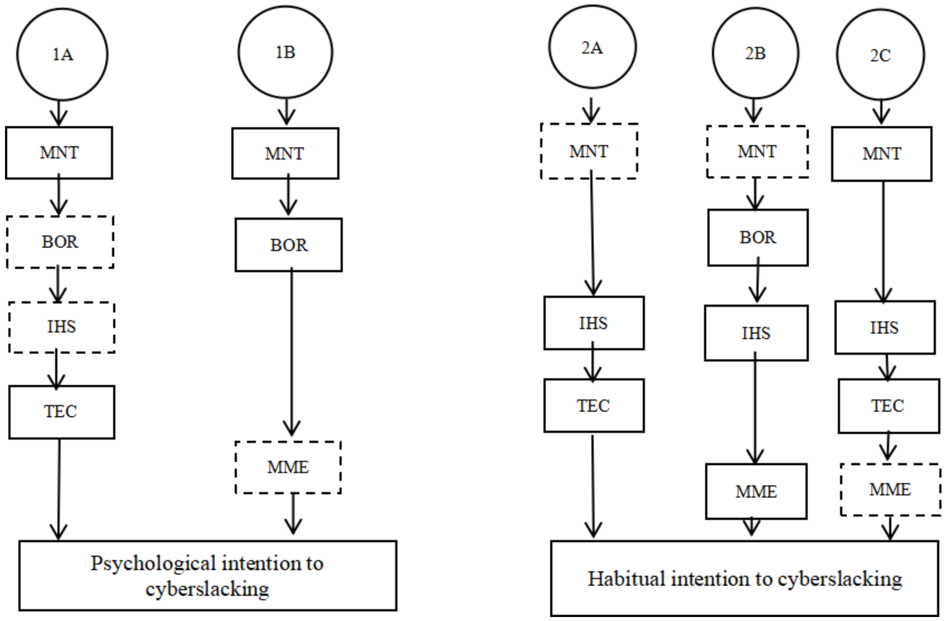

Figure 2. Visual presentation of the configurational pathways to cyberslacking (the arrows represent a sequence; lined boxes explain the presence of the variables; dotted boxes explain both presence and absence of the variables; and no box explains the absence of the variables)

positive thing. On the other hand, only 28.73 percent have viewed cyberslacking negatively, which implies that these students are aware of the side effects of their actions.

To obtain insight into the influence of culture, sentiment analysis was performed on two of the previously mentioned groups of students based on our fsQCA analysis. The results of sentiment analysis show that although students with both psychological intention and habitual intention show a positive sentiment towards cyberslacking, higher positivity is evident among students from Bangladesh with a psychological intention. This may be because of the cultural diversity of student cognition and behaviour [36]. Interestingly, students coming from India and South Africa show neutral sentiment towards cyberslacking. This difference in sentiment according to respondents nationality is important as it provides preliminary evidence that cyberslacking sentiment varies based on culture. Examining the reasons for this represents a valuable avenue of research for scholars. From text mining, we also see that students with the habitual intention of cyberslacking use more negative words than students with the psychological intention. It is because their habitual attitudes, beliefs, and behaviors differ from each other [37]. Compared to the Bengali students, the students coming from the USA showed more negative sentiment towards cyberslacking in terms of their habitual beliefs (for example, one should not disrespect the faculty by not paying attention). However, further studies are needed to study the underlying causes for such cultural differences in cyberslacking literature.

From this analysis we can summarize that students with high mental health problems show less positive sentiment compared to students with high internet habit strength. The results show that most of the students at the universities may not be able to adapt to the new trends of education, which is why they think their cyberslacking behavior is justified and not harmful. The total number of sentiments represent 20.85 percent of the total number of university students. We also tried to extract some common comments from the opinions of university students. Interestingly, most of the students think reducing class time and making classes more interactive and entertaining might reduce their cyberslacking behavior. However, from our fsQCA analysis, we found that along with student internet habits, their mental health problems (substance use disorders, stressful experience and depression) also increase their cyberslacking intentions. Therefore, combining the results from fsQCA and sentiment analysis focusing on cultural diversity, we can come up with the causal recipe that leads to university student cyberslacking behavior and also show how they feel about their cyberslacking intention.

Table 3. The sentiment analysis of university students

Sentiments	Response	Percentage
Positive	62	71.26
Negative	25	28.73
Total sentiments	87	100
Total response across total university students		20.85

6. Conclusions and Implications

Drawing on fsQCA and the sentiment analysis, this study for the first time empirically examines the combination of conditions that are sufficient to explain university student intentions toward cyberslacking during COVID-19. From the fsQCA analysis, we found five pathways and two categories of students explaining their individual intention toward cyberslacking. From the sentiment analysis, we found that those two categories of students show positive sentiment regarding their cyberslacking behavior despite having the knowledge that cyberslacking is harmful. These findings advance empirical and practical understanding of the pathways through which we can identify student behavioral intentions toward cyberslacking.

The implications of this paper are twofold. First, the implication for the academics. This study investigates cyberslacking behavior among undergraduate students and contributes to the pedagogy and literature of worse-usage of internet by the students during their schedule classes. As for theoretical implications, this study examines both the theory of planned behavior and social learning theory and contributes toward understanding student attitudes of using internet for non-academic purposes during class time. Most significantly, this study will enhance understanding for the technology-adoption theory. Second, as for implications for educators, this study is very timely since major portions of the classes, especially at the undergraduate level, are taking place on the internet during the recent pandemic. Hence, understanding student intentions for cyberslacking will assist educators for realizing how to design their lesson and, above all, allow the educators to plan proactively to involve students for productive performance during the classes. Both the results from sentiment analysis and FsQCA analysis would give a first-hand understanding to educators to do a fresh start for reducing student cyberslacking behavior considering the cultural factors and changing circumstances in pandemic.

In addition, this study extends research on student behavior and cyberslacking from the COVID-19 perspective. By using QCA and NLP, this study offers an alternative perspective to the education and information science literature. The new perspectives from this study could inspire future studies based on cultural differences to examine the configuration of conditions for other groups of people in terms of age or occupation, since the context of the current education status of students has been identified as an incumbent factor too. In spite of the contributions, this study has a few limitations. First, the study utilized only the QCA and sentiment analysis. Though the use of QCA and sentiment analysis brings a new angle to cyberslacking research, future studies can employ more quantitative methods to examine this phenomenon. Second, the study is limited to constructs identified from extant research, thus future research can explore the configuration of other conditions that are not captured in this study. Lastly, this study collects data using survey questionnaires of student opinions. Therefore, future studies are advised to utilize longitudinal or panel data to improve the reliability and validity of the outcome.

References

[1] M. Aybas and A. Gungor, "Does cyberloafing reduce academic performance? a comparative study between turkey and poland," *Revista Argentina de Clínica Psicológica*, vol. 29, no. 5, pp. 1060–1072, 2020.

[2] J. Vitak, J. Crouse, and R. LaRose, "Personal internet use at work: Understanding cyberslacking," *Computers in Human Behavior*, vol. 27, no. 5, pp. 1751–1759, 2011.

[3] M. M. Dmoura, H. S. Bakarb, and M. R. Hamzahc, "An antecedent, consequences, and policies view of cyber loafing among students," *International Journal of Innovation, Creativity and Change*, no. 2 (11), p. 325, 2020.

[4] C. Romero-Blanco, J. Rodríguez-Almagro, M. D. Onieva-Zafra, M. L. Parra-Fernández, M. D. C. Prado-Laguna, and A. Hernández-Martínez, "Physical activity and sedentary lifestyle in university students: Changes during confinement due to the covid-19 pandemic," *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, p. 6567, 2020.

[5] R. Winkler, S. Hobert, T. Fischer, A. Salovaara, M. Söllner, and J. M. Leimeister, "Engaging learners in online video lectures with dynamically scaffolding conversational agents," Association for Information Systems, 2020.

[6] A. E. Flanigan and K. A. Kiewra, "What college instructors can do about student cyber-slacking," *Educational Psychology Review*, vol. 30, no. 2, pp. 585–597, 2018.

[7] Ş. Gökçearslan, Ç. Uluyol, and S. Şahin, "Smartphone addiction, cyberloafing, stress and social support among university students: A path analysis," *Children and Youth Services Review*, vol. 91, pp. 47–54, 2018.

[8] Y. Akbulut, O. Dönmez, and Ö. Ö. Dursun, "Cyberloafing and social desirability bias among students and employees," *Computers in Human Behavior*, vol. 72, pp. 87–95, 2017.

[9] J. Wu, W. Mei, and J. C. Ugrin, "Student cyberloafing in and out of the classroom in china and the relationship with student performance," *Cyberpsychology, Behavior, and Social Networking*, vol. 21, no. 3, pp. 199–204, 2018.

[10] A. Taneja, V. Fiore, and B. Fischer, "Cyber-slacking in the classroom: Potential for digital distraction in the new age," *Computers & Education*, vol. 82, pp. 141–151, 2015.

[11] B. Rihoux and C. C. Ragin, *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. Sage Publications, 2008.

[12] I. O. Pappas, P. Mikalef, M. N. Giannakos, and P. E. Kourouthanassis, "Explaining user experience in mobile gaming applications: an fsqca approach," *Internet Research*, 2019.

[13] M. Saritepeci, "Predictors of cyberloafing among high school students: unauthorized access to school network, metacognitive awareness and smartphone addiction," *Education and Information Technologies*, pp. 1–19, 2019.

[14] C. Brod, *Technostress: The human cost of the computer revolution*. Reading, Mass.: Addison-Wesley, 1984.

[15] A. N. Çoklar and Y. L. Sahin, "Technostress levels of social network users based on icts in turkey," *European Journal of Social Sciences*, vol. 23, no. 2, pp. 171–182, 2011.

[16] U. Güğerçin, "Does techno-stress justify cyberslacking? an empirical study based on the neutralisation theory," *Behaviour & Information Technology*, vol. 39, no. 7, pp. 824–836, 2020.

[17] Y. B.-D. Kolikant, "Digital natives, better learners? students' beliefs about how the internet influenced their ability to learn," *Computers in Human Behavior*, vol. 26, no. 6, pp. 1384–1391, 2010.

[18] C.-S. Ang, "Internet habit strength and online communication: Exploring gender differences," *Computers in Human Behavior*, vol. 66, pp. 1–6, 2017.

[19] D. Ding, B. del Pozo Cruz, M. A. Green, and A. E. Bauman, "Is the covid-19 lockdown nudging people to be more active: a big data analysis," 2020.

[20] M. Zimmermann, C. Bledsoe, and A. Papa, "The impact of the covid-19 pandemic on college student mental health: A longitudinal examination of risk and protective factors," 2020.

[21] B. K. Mercado, C. Giordano, and S. Dilchert, "A meta-analytic investigation of cyberloafing," *Career Development International*, 2017.

[22] R. Yılmaz and H. Yurdugül, "Cyberloafing in it classrooms: exploring the role of the psycho-social environment in the classroom, attitude to computers and computing courses, motivation and learning strategies," *Journal of Computing in Higher Education*, vol. 30, no. 3, pp. 530–552, 2018.

[23] M. Finkielsztein, "Class-related academic boredom among university students: a qualitative research on boredom coping strategies," *Journal of Further and Higher Education*, vol. 44, no. 8, pp. 1098–1113, 2020.

[24] A. Bandura, "The evolution of social cognitive theory," *Great minds in management*, pp. 9–35, 2005.

[25] E. Simanjuntak, N. A. F. Nawangsari, and R. Ardi, "Do students really use internet access for learning in the classroom?: Exploring students' cyberslacking in an indonesian university," *Behavioral Sciences*, vol. 9, no. 12, p. 123, 2019.

[26] R. A. Faisal, M. C. Jobe, O. Ahmed, and T. Sharker, "Mental health status, anxiety, and depression levels of bangladeshi university students during the covid-19 pandemic," *International Journal of Mental Health and Addiction*, pp. 1–16, 2021.

[27] X. Wang, S. Hegde, C. Son, B. Keller, A. Smith, and F. Sasangohar, "Investigating mental health of us college students during the covid-19 pandemic: cross-sectional survey study," *Journal of medical Internet research*, vol. 22, no. 9, p. e22817, 2020.

[28] R. M. O'brien, "A caution regarding rules of thumb for variance inflation factors," *Quality & quantity*, vol. 41, no. 5, pp. 673–690, 2007.

[29] I. O. Pappas, M. N. Giannakos, and D. G. Sampson, "Fuzzy set analysis as a means to understand users of 21st-century learning systems: The case of mobile learning and reflections on learning analytics research," *Computers in Human Behavior*, vol. 92, pp. 646–659, 2019.

[30] C. C. Ragin, "Set relations in social research: Evaluating their consistency and coverage," *Political analysis*, pp. 291–310, 2006.

[31] C. Q. Schneider and C. Wagemann, "Standards of good practice in qualitative comparative analysis (qca) and fuzzy-sets," *Comparative Sociology*, vol. 9, no. 3, pp. 397–418, 2010.

[32] T. Ragu-Nathan, M. Tarafdar, B. S. Ragu-Nathan, and Q. Tu, "The consequences of technostress for end users in organizations: Conceptual development and empirical validation," *Information systems research*, vol. 19, no. 4, pp. 417–433, 2008.

[33] J. Dul, "Necessary condition analysis (nca) logic and methodology of "necessary but not sufficient" causality," *Organizational Research Methods*, vol. 19, no. 1, pp. 10–52, 2016.

[34] P. C. Fiss, "Building better causal theories: A fuzzy set approach to typologies in organization research," *Academy of management journal*, vol. 54, no. 2, pp. 393–420, 2011.

[35] C. K. Pastor, "Sentiment analysis of filipinos and effects of extreme community quarantine due to coronavirus (covid-19) pandemic," *Available at SSRN 3574385*, 2020.

[36] J. Burrell, Z. Kahn, A. Jonas, and D. Griffin, "When users control the algorithms: values expressed in practices on twitter," *Proceedings of the ACM on Human-Computer Interaction*, vol. 3, no. CSCW, pp. 1–20, 2019.

[37] J. Vitak, J. Crouse, and R. LaRose, "Personal internet use at work: Understanding cyberslacking," *Computers in Human Behavior*, vol. 27, no. 5, pp. 1751–1759, 2011.