Research Square

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Prolonged Use of Computing Devices and Computer Vision Syndrome Among University Lecturers During the Covid-19 Pandemic in Malaysia: A Cross-Sectional Study

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Abstract

Objective

To determine the prevalence of computer vision syndrome (CVS) and its associated factors among university lecturers in Malaysia during the COVID-19 pandemic.

Methods

A cross-sectional study was conducted among 174 lecturers from Universiti Putra Malaysia (UPM) and Universiti Teknologi MARA (UITM) between March and May 2021. A self-administered questionnaire, validated and pretested among 40 respondents, was used to collect data on sociodemographic characteristics, working characteristics, working conditions, and computer vision syndrome (CVS) symptoms. Chi-square tests and multivariable logistic regression were used to examine associations between the study variables and CVS. Exploratory machine-learning models were also constructed to examine the combined contribution of these factors to CVS.

Results

The prevalence of CVS was 77.6% (135/174). The most frequently reported symptoms were eye fatigue (52.3%), headache (44.3%), and eye strain (43.1%). University, working hours, seating distance, computer glasses, eye examination, and eye lubrication were associated with CVS in the chi-square analysis. In the multivariable logistic regression, only university affiliation remained an independent predictor of CVS (aOR = 2.79, 95% CI: 1.27–6.11, p = 0.010), with UITM lecturers having approximately 2.8 times higher odds of CVS compared with UPM lecturers. In the exploratory machine-learning analysis, the random forest model achieved the best overall performance (AUC = 0.70), with university, working hours during COVID-19, and seating distance identified as the leading predictors.

Conclusion

CVS was highly prevalent among university lecturers during the COVID-19 pandemic. University affiliation was the only independent predictor of CVS after adjustment for confounders. Work-related and workstation-related factors were associated with CVS and should be considered in occupational health interventions targeting lecturers who work long hours with computing devices.

1. Introduction

The Coronavirus disease 2019 (COVID-19) pandemic was an outbreak that reached international borders and affected individuals on a global scale. The pandemic caused university lecturers to work from home (WFH) and conduct their work tasks using computing devices. The trend of learning and working on the

internet increased during the pandemic, and higher learning institutions shifted teaching and learning activities to online or remote modes (Selvanathan et al., 2023). Increased digital-device use during the COVID-19 period also raised concerns about digital-device-related ocular health (Bahkir & Grandee, 2020; Ganne et al., 2021). Statistics from the Department of Statistics Malaysia in 2020 showed that internet access among Malaysians reached 90.1% (Department of Statistics Malaysia, 2020). From the perspective of work productivity and health, computer vision syndrome can reduce work productivity and cause visual-related problems such as eye strain and redness of the eyes (Coles-Brennan et al., 2019).

Computer vision syndrome, also known as digital eye strain, refers to a group of eye- and vision-related problems associated with prolonged use of computers, tablets, e-readers and cell phones (Sheppard & Wolffsohn, 2018; Kaur et al., 2022). When watching digital screens for a longer period of time, people may experience eye pain and vision problems. CVS symptoms have been classified into four categories: asthenopia, ocular surface-related symptoms, visual symptoms, and extra-ocular symptoms (Blehm et al., 2005). More recently, CVS has also been described as encompassing ocular, musculoskeletal, and behavioural conditions resulting from prolonged use of digital screens (Kahal & Darra, 2025).

Based on the present literature, the factors that influence computer vision syndrome include sociodemographic factors, work characteristics, and working conditions. A recent study among non-academic university staff in Nigeria similarly identified excessive screen exposure as a significant risk factor for visual impairment, highlighting the occupational relevance of this issue across different university personnel categories (Eni & Uahomo, 2024). For sociodemographic factors, previous studies found that female respondents were more prone to CVS than male respondents (Assefa et al., 2017), and people aged 30 years and above had a higher risk of CVS compared with younger people (Assefa et al., 2017). Other sociodemographic characteristics have also been examined in relation to CVS across different populations (Anbesu & Lema, 2023).

For work characteristics, people working on computing devices for more than 5 hours have a higher risk of CVS compared with people working less than 5 hours a day (Assefa et al., 2017; Dessie et al., 2018; Adane et al., 2022).

For working conditions, improper sitting position was 2.3 times more likely to be associated with CVS (Assefa et al., 2017). People who had not taken a break within 20 minutes suffered more significantly from CVS (Assefa et al., 2017). Screen position, viewing distance, break habits, and other ergonomic factors have also been reported to be associated with CVS symptoms (Dessie et al., 2018; Gasheya et al., 2024).

2. Materials and Method

This was a cross-sectional study conducted among lecturers from Universiti Putra Malaysia and Universiti Teknologi MARA.

2.1 Study Population and Location

The study was conducted in Malaysia, specifically at Universiti Putra Malaysia and Universiti Teknologi MARA. Universiti Putra Malaysia and Universiti Teknologi MARA were universities that implemented working from home (WFH) and learning from home during the COVID-19 pandemic (Selvanathan et al., 2023; Mohd Salleh et al., 2023).

2.2 Sampling Method and Sample Size

A simple random sampling method was employed. The sampling frame consisted of all 288 full-time lecturers at the two universities. A list of lecturers was obtained from the staff directory available on each university's official website, and participants were randomly selected from this list. A total of 177 questionnaires were returned, of which 3 were excluded based on the exclusion criteria, resulting in a final sample of 174 participants.

The minimum required sample size was calculated using the prevalence formula: $n = Z^2 \times P(1-P) / d^2$ where Z = 1.96 (95% confidence level), P = 0.899 (expected prevalence based on previous literature on asthenopia among computer users), and d = 0.05 (margin of error). This yielded a minimum required sample size of 150 participants. The final achieved sample of 174 participants exceeded this minimum requirement.

2.3 Questionnaire

The questionnaire was adapted from items used in recent studies on computer vision syndrome, work characteristics, working conditions, and CVS symptoms (Assefa et al., 2017; Dessie et al., 2018). The questionnaire included sociodemographic characteristics (I), work characteristics (II), working conditions (III), and symptoms of CVS (IV). The data collected in sections II and III provided information on knowledge and practice in the use of computing devices. Section IV provided information on CVS symptoms among lecturers during COVID-19. The sociodemographic characteristics included university name, gender, age, race, marital status and teaching experience. For the work characteristics, the variables included the use of visual aids, type of computing device, working hours before COVID-19, and working hours during COVID-19. The working conditions included the use of antiglare or blue-light protection, use of computer glasses, eye examination, working at night, working during the day, turning on the light, sufficient lighting, short breaks while using computing devices, seating position with computing devices, eye lubrication, comfortable screen position, comfortable air ventilation, and comfortable screen contrast. The symptoms of computer vision syndrome in the questionnaire were eye strain, blurred distance vision, headache, redness of eye, double vision, dry eyes, eye fatigue, eye itching, and eye tearing.

The pilot study was conducted among 40 lecturers at Universiti Putra Malaysia, and the questionnaire was edited for easier understanding by the respondents. The internal consistency of the CVS symptom scale was assessed using Cronbach's alpha, yielding a coefficient of 0.890, indicating excellent internal consistency (Tavakol & Dennick, 2011).

The questionnaire was randomly distributed to lecturers at each university via an online platform. The online platform used in this study was Google Form. The questionnaire was distributed to the lecturers at Universiti Putra Malaysia and Universiti Teknologi MARA via email addresses obtained from the website of each university. The questionnaire was selected based on the inclusion and exclusion criteria after submission. Respondents who did not comply with the inclusion and exclusion criteria were excluded.

2.4 Inclusion and Exclusion Criteria

For the inclusion criteria, lecturers who were validated to take part were full-time lecturers at Universiti Putra Malaysia and Universiti Teknologi MARA and had more than one year of working experience at these universities.

The respondents excluded from the study were those who had symptoms or signs of computer vision syndrome before using computing devices and those with ocular diseases such as glaucoma and conjunctivitis.

2.5 Ethical Consideration

Ethical approval to conduct the study was obtained from JKEUPM. Permission to collect data at Universiti Teknologi MARA was obtained from the representative lecturer at Universiti Teknologi MARA.

2.6 Statistical and Machine-Learning Analysis

Descriptive statistics were used to summarize the characteristics of the respondents. Categorical variables were presented as frequency and percentage. The associations between sociodemographic characteristics, work characteristics, working conditions, and computer vision syndrome were examined using the chi-square test. A *p-value* of < 0.05 was considered statistically significant. The Phi coefficient (φ) was reported as a measure of effect size for all chi-square analyses, with values interpreted as negligible (φ < 0.10), small (φ = 0.10–0.30), or moderate (φ > 0.30) (Kim, 2017). To identify independent predictors of CVS, a multivariable logistic regression analysis was performed using the Enter method. Variables that were statistically significant in the chi-square analysis ($p < 0.05$) were entered into the multivariable model. Adjusted odds ratios (aOR) with 95% confidence intervals (CI) were reported.

Machine-learning models were used to further examine the combined contribution of sociodemographic characteristics, work characteristics, and working conditions to the occurrence of computer vision syndrome. The outcome variable was CVS status, defined as the presence of at least one CVS symptom. This definition was consistent with previous occupational studies on CVS (Assefa et al., 2017; Dessie et al., 2018) and was adopted to allow comparability with the existing literature. The candidate predictors included university, gender, age group, marital status, teaching experience, type of computing device, use of visual aids, working hours before and during COVID-19, and working-condition variables. Categorical variables were encoded before model development.

Three supervised models were constructed, including penalized logistic regression, random forest, and support vector machine. Model performance was estimated using stratified 10-fold cross-validation. The area under the receiver operating characteristic curve, accuracy, sensitivity, specificity, and F1-score were used to evaluate model performance. ROC curves were generated to compare model discrimination, and variable importance was derived from the random forest model.

3. Results

A total of 177 questionnaires were answered, and 3 were excluded because the respondents met the exclusion criteria of having eye problems such as glaucoma. Therefore, 174 respondents were included in the final analysis.

3.1. Descriptive Analysis

The analysis of socio-demographic characteristics was based on 174 respondents. The sociodemographic characteristics included university, gender, age, race, marital status, and teaching experience.

Table 1 shows that 75 respondents (43.1%) were from Universiti Putra Malaysia (UPM), while 99 respondents (56.9%) were from Universiti Teknologi MARA (UITM). Most respondents were female [132 respondents (75.9%)] compared with male [42 respondents (24.1%)]. Based on ethnicity, most respondents were Malay [158 respondents (90.8%)], followed by Chinese [12 respondents (6.9%)], Indian [2 respondents (1.1%)], and others [2 respondents (1.1%)].

For age group, 9 respondents (5.2%) were aged 20–30 years, 103 respondents (59.2%) were aged 31–40 years, 48 respondents (27.6%) were aged 41–50 years, and 14 respondents (8.0%) were aged 51–60 years. A total of 39 respondents (22.4%) were single, while 135 respondents (77.6%) were married. Most respondents used visual aids such as spectacles and contact lenses [149 respondents (85.6%)], while 25 respondents (14.4%) did not use any visual aids. For teaching experience, 103 respondents (59.2%) had 11–20 years of teaching experience, 66 respondents (37.9%) had 1–10 years of teaching experience, and 5 respondents (2.9%) had 21–30 years of teaching experience.

Table 1
Descriptive Analysis for Socio Demographic.

		Frequency	Percentage (%)
University	UPM	75	43.1
	UITM	99	56.9
Gender	Male	42	24.1
	Female	132	75.9
Age	20–30 Years	9	5.2
	31–40 Years	103	59.2
	41–50 Years	48	27.6
	51–60 Years	14	8
Race	Malay	158	90.8
	Chinese	12	6.9
	Indian	2	1.1
	Other	2	1.1
Status	Single	39	22.4
	Married	135	77.6
Teaching Experience	1–10 Years	66	37.9
	11–20 Years	103	59.2
	21–30 Years	5	2.9

The working characteristics of the 174 respondents were recorded as frequency and percentage. The working characteristics included computing device, visual aids, working hours before COVID-19, and working hours during COVID-19 per day.

Table 2 shows that the most commonly used computing device was laptop [135 respondents (77.6%)], followed by computer [29 respondents (16.7%)] and smartphone [10 respondents (5.7%)]. Before the COVID-19 pandemic, 98 respondents (56.3%) worked with computing devices for 1–4 hours per day, while 76 respondents (43.7%) worked for 5–8 hours per day. During the COVID-19 pandemic, 163 respondents (93.7%) worked with computing devices for 5–8 hours per day, while only 11 respondents (6.3%) worked for 1–4 hours per day.

Table 2
Descriptive Analysis for Work Characteristic.

		Frequency	Percentage (%)
Computing Device	Computer	29	16.7
	Laptop	135	77.6
	Smartphone	10	5.7
Visual Aids	Yes	149	85.6
	No	25	14.4
Working hours before COVID-19 per day	1–4 Hours	98	56.3
	5–8 Hours	76	43.7
Working hours during COVID-19 per day	1–4 hours	11	6.3
	5–8 hours	163	93.7

The working conditions of the respondents were recorded from the questionnaire. The respondents were given five choices: never, rarely, sometimes, often and always. The working conditions recorded were the use of antiglare or blue-light protection, use of computer glasses, eye examination, working at night, working during the day, turning on the light, sufficient lighting, short breaks while using computing devices, seating position with computing devices, eye lubrication, screen position, air ventilation, and screen contrast. Table 3 shows the data from the respondents.

Table 3
Descriptive Analysis for Working Conditions

		Frequency	Percentage (%)
Use of antiglare or blue-light protection	Never	113	64.9
	Rarely	16	9.2
	Sometimes	13	7.5
	Often	9	5.2
	Always	23	13.2
Use of computer glasses	Never	92	52.9
	Rarely	27	15.5
	Sometimes	16	9.2
	Often	16	9.2
	Always	23	13.2
Eye examination	Never	17	9.8
	Rarely	34	19.5
	Sometimes	103	59.2
	Often	12	6.9
	Always	8	4.6
Working at night	Never	7	4
	Rarely	10	5.7
	Sometimes	86	49.4
	Often	52	29.9
	Always	19	10.9
Working during the day	Never	4	2.3
	Rarely	4	2.3
	Sometimes	20	11.5
	Often	100	57.5
	Always	46	26.4
Turn on light	Never	3	1.7
	Rarely	4	2.3

	Sometimes	52	29.9
	Often	73	42
	Always	42	24.1
Sufficient lighting	Rarely	7	4
	Sometimes	55	31.6
	Often	76	43.7
	Always	36	20.7
Short break while using computing devices	Rarely	19	10.9
	Sometimes	97	55.7
	Often	39	22.4
	Always	19	10.9
Seating position with computing devices	Never	14	8
	Rarely	36	20.7
	Sometimes	101	58
	Often	19	10.9
	Always	4	2.3
Eye lubrication	Never	123	70.7
	Rarely	21	12.1
	Sometimes	21	12.1
	Often	9	5.2
Comfortable with screen position	Rarely	11	6.3
	Sometimes	92	52.9
	Often	60	34.5
	Always	11	6.3
Comfortable with air ventilation	Never	8	4.6
	Rarely	6	3.4
	Sometimes	94	54
	Often	53	30.5
	Always	13	7.5

Comfortable with screen contrast	Never	1	0.6
	Rarely	9	5.2
	Sometimes	89	51.1
	Often	62	35.6
	Always	13	7.5

Table 4 shows the prevalence of symptoms of computer vision syndrome. The frequency was the percentage of respondents who reported each symptom, while the magnitude was the number of respondents with the symptom.

The most common symptoms were eye fatigue [91 respondents (52.3%)], headache [77 respondents (44.3%)], eye strain [75 respondents (43.1%)], blurred distance vision [64 respondents (36.8%)], and eye itching [49 respondents (28.2%)]. Other symptoms included dry eyes [48 respondents (27.6%)], eye tearing [42 respondents (24.1%)], redness of eye [33 respondents (19.0%)], and double vision [28 respondents (16.1%)].

3.2. Prevalence of Computer Vision Syndrome

Table 4
Prevalence of Computer Vision Syndrome's Symptoms

Eyes strain	**Magnitude**	**Frequency, f (%)**	**Mean**	**±SD**
	75	**43.1**	**0.431**	**0.49665**
Blurred distance vision	64	36.8	0.3678	0.4836
Headache	77	44.3	0.4425	0.49812
Redness of eye	33	19	0.1897	0.39316
Double vision	28	16.1	0.1609	0.36852
Dry eyes	48	27.6	0.2759	0.44824
Eye fatigue	91	52.3	0.523	0.50091
Eye itching	49	28.2	0.2816	0.45108
Eye tearing	42	24.1	0.2414	0.42915

The prevalence of the computer vision syndrome was calculated by selecting respondents who had at least one symptom of computer vision syndrome. Based on this calculation, the prevalence of CVS was 77.6%, with a magnitude of 135 respondents.

3.3 The Relationship Between Socio-Demographic Characteristics, Work Characteristics, Working Conditions,

and Computer Vision Syndrome

The relationship between socio-demographic characteristics and the occurrence of computer vision syndrome among lecturers was analysed according to categories based on university, age, and status of respondents, as shown in Table 5. The data were analysed using chi-square test, and the significant value was set at $p < 0.05$. Only university was significantly associated with the occurrence of computer vision syndrome ($p = 0.003$). The other variables, such as age and marital status, did not show significant association with the occurrence of computer vision syndrome ($p > 0.05$).

Table 5
The Relationship Between Socio-Demographic Characteristics and Computer Vision Syndrome

		Computer Vision Syndrome				
		No	**Yes**	$\varvec{\chi^2}$	***p*-value**	$\varvec{\varphi}$
University	UPM	25(16.8)	50(58.2)	9.038	0.003	0.228
	UITM	14(22.2)	85(76.8)			
Age	40 and below	27(25.1)	85(86.9)	0.518	0.472	0.055
	Above 40	12(13.9)	50(48.1)			
Status	Single	9(8.7)	30(30.3)	0.013	0.910	0.009
	Married	30(30.9)	105(104.7)			

The relationship between working characteristics and the occurrence of computer vision syndrome among lecturers was analysed according to visual aids and working hours. Based on Table 6, the chi-square test was used, and the significant value was set at $p < 0.05$. Visual aids were not significantly associated with CVS ($p = 0.750$), while working hours were significantly associated with CVS ($p = 0.049$).

Table 6
The Relationship Between Work Characteristics and Computer Vision Syndrome

		Computer Vision Syndrome				
		No	Yes	Total	*p-value*	$\varvec{\varphi}$
Visual Aid	Yes	34(33.4)	115(115.6)	149	0.75	0.024
	No	5(5.6)	20(19.4)	25		
Working Hour	1–4 Hours	5(2.5)	6(8.50)	11	0.049	0.149
	5–8 Hours	34(36.5)	129(126.5)	163		

Table 7 shows the association between working condition and computer vision syndrome. The working conditions recorded were the use of antiglare and blue-light protection, use of computer glasses, eye examination, working at night, working during the day, turning on the light during working, sufficient lighting, taking short breaks while using computing devices, seating distance from the computing device, use of eye lubrication, good sitting position, air ventilation, and screen contrast. The data were analysed using the chi-square test, and the significant value was set at $p < 0.05$. Use of computer glasses ($p = 0.037$), eye examination ($p = 0.030$), seating distance from the computing device ($p = 0.013$), and use of eye lubrication ($p = 0.023$) were significantly associated with CVS. Other working condition variables did not show significant association with CVS.

Table 7
The Relationship Between Working Conditions and Computer Vision Syndrome

		No	Yes	x^2	*p*-value	\varvec$\varphi$
Use of antiglare and blue-light protection	No	35(28.9)	94(100.1)	6.385	0.12	0.192
	Yes	4(10.1)	41(34.9)			
Use of computer glasses	No	32(26.7)	87(92.3)	4.339	0.037	0.158
	Yes	7(12.3)	48(42.7)			
Eye examination	No	6(11.4)	45(39.6)	4.705	0.03	0.164
	Yes	33(27.6)	90(95.4)			
Working at night	No	1(3.8)	16(13.2)	3.79	0.052	0.148
	Yes	38(35.2)	119(121.8)			
Working in day	No	1(1.8)	7(6.2)	0.537	0.464	0.056
	Yes	38(37.2)	128(128.8)			
Turn on light during working	No	1(1.6)	6(5.4)	0.306	0.58	0.042
	Yes	38(37.4)	129(129.6)			
Use of sufficient lighting	No	1(1.6)	6(5.4)	0.306	0.58	0.042
	Yes	38(37.4)	129(129.9)			
Taking a short break from using computing devices	No	3(4.3)	16(14.7)	0.578	0.447	0.058
	Yes	36(34.7)	119(120.3)			
Seating too close to the computing device	No	5(11.2)	45(38.8)	6.217	0.013	0.189
	Yes	34(27.8)	90(96.2)			
Use of eye lubrication	No	37(32.3)	107(111.7)	5.169	0.023	0.172
	Yes	2(6.7)	28(23.3)			
Good sitting position	No	2(2.7)	10(9.3)	0.261	0.609	0.039
	Yes	37(36.3)	125(125.7)			
Good air ventilation	No	3(3.1)	11(10.9)	0.009	0.926	0.007
	Yes	36(35.9)	124(124.1)			
Good screen contrast	No	3(2.2)	7(7.8)	0.329	0.566	0.043
	Yes	36(36.8)	128(127.2)			

3.4 Multivariable Logistic Regression Analysis

Multivariable logistic regression was performed to identify independent predictors of CVS. Variables significantly associated with CVS in the chi-square analysis were entered into the model, including university, working hours during COVID-19, use of computer glasses, eye examination, seating distance from the computing device, and use of eye lubrication. After adjusting for all variables in the model, only university affiliation remained an independent predictor of CVS (aOR = 2.79, 95% CI: 1.27–6.11, p = 0.010). Lecturers from Universiti Teknologi MARA had approximately 2.8 times higher odds of CVS compared with those from Universiti Putra Malaysia. The other variables did not retain statistical significance after adjustment, suggesting that their associations with CVS may be partially explained by confounding factors. The results of the multivariable logistic regression are presented in Table 8.

Table 8
Multivariable Logistic Regression Analysis for Predictors of Computer Vision Syndrome

Variable	**aOR**	**95% CI**	***p-value***
University (UITM vs UPM)	2.79	1.27–6.11	0.010*
Working hours during COVID-19	2.01	0.49–8.18	0.332
Use of computer glasses	2.19	0.85–5.65	0.105
Eye examination	0.50	0.18–1.40	0.188
Seating distance	0.53	0.18–1.59	0.259
Use of eye lubrication	3.65	0.79–16.81	0.097

3.5 Machine-Learning Analysis

Machine-learning models were constructed to examine the occurrence of CVS using sociodemographic characteristics, work characteristics, and working conditions. The performance of the three models is summarized in Table 9. The random forest model showed the best overall performance, with an AUC of 0.70, accuracy of 0.74, sensitivity of 0.84, specificity of 0.38, and F1-score of 0.83. The penalized logistic regression model had an AUC of 0.68, while the support vector machine model had an AUC of 0.65. The ROC curves of the three models are presented in Fig. 1A.

The random forest model was further used to rank the predictors of CVS. University, working hours during COVID-19, seating distance from the computing device, use of eye lubrication, eye examination, and use of computer glasses were the leading predictors. Working at night, use of antiglare or blue-light protection, short breaks while using computing devices, and visual aids also contributed to the model but showed lower relative importance. The variable-importance ranking is presented in Fig. 1B.

Table 9
Performance of Machine-Learning Models for Predicting Computer Vision Syndrome

Model	AUC	Accuracy	Sensitivity	Specificity	F1-score
Penalized logistic regression	0.68	0.71	0.81	0.36	0.82
Random forest	0.70	0.74	0.84	0.38	0.83
Support vector machine	0.65	0.69	0.79	0.33	0.80

4. Discussion

Of the 174 respondents, most respondents were from UITM, followed by UPM. The participants were mostly female, and most respondents were aged between 31 and 40 years. Recent evidence suggests that sex may be associated with the occurrence of CVS among digital-device users (Anbesu & Lema, 2023). The respondents were mostly Malay and married, reflecting the demographic composition of the study sample.

From the study, lecturers were more comfortable working with laptops rather than computers, as laptops have the advantage of mobility. The lecturers also used visual aids such as contact lenses and spectacles. The working hours with computing devices increased during COVID-19 compared with before COVID-19 due to working from home (WFH) among lecturers.

The finding revealed that 77.6% of the 174 respondents had computer vision syndrome. The result was consistent with recent studies and systematic reviews reporting a high prevalence of computer vision syndrome among digital-device users (Wang et al., 2021; Ccami-Bernal et al., 2024; León-Figueroa et al., 2024). The most contributing symptoms to the occurrence of computer vision syndrome were eye fatigue, headache, eye strain, and blurred vision. Similar symptoms were also reported in recent studies on digital eye strain among computer users (Alatawi et al., 2022; Mohan et al., 2021).
The result showed that workplace was significantly associated with computer vision syndrome. The Universiti Putra Malaysia is a research university, while Universiti Teknologi MARA is more teaching-oriented. The difference between teaching and research universities may influence the number of classes and teaching-related tasks conducted using computing devices. A higher number of classes may be associated with greater screen exposure and a higher occurrence of computer vision syndrome. Age and marital status were not significantly associated with computer vision syndrome. This may be because the study population only included lecturers, who were mostly female and Malay, so no significant difference could be established due to the homogeneity of the sampling population.

Visual Aids, such as spectacle and contact lenses, were not significantly associated with computer vision syndrome in this study. However, the research by Assefa et al. (2017) showed that visual aids had a significant association with computer vision syndrome, with a *p-value* of 0.001. The difference in findings may be due to the type of study population, as Assefa et al. (2017) studied bank workers, while recent studies also included students and other digital-device users (Alatawi et al., 2022).

The result showed that most lecturers never wore computer glasses and did not regularly use eye lubrication and blue light protection. This may indicate a lack of awareness among lecturers regarding eye safety while working with computing devices. To protect lecturers from occupational hazards, the hierarchy of control can be considered, including engineering control such as blue-light and anti-glare protection, and personal protective equipment such as computer glasses, based on Centers for Disease Control and Prevention (2024). Eye lubrication was associated with CVS in this study and may also be considered as a supportive measure to reduce eye discomfort.

There was a significant association between working hours and CVS based on the result. Long working hours during the COVID-19 pandemic were significantly associated with CVS. This finding was consistent with recent studies, which reported that longer exposure to computing devices was associated with a higher occurrence of computer vision syndrome (Dessie et al., 2018).

The use of computer glasses and frequent eye examination were associated with lower odds of CVS in this study. Recent reviews on digital eye strain have emphasized proper refractive correction, regular eye care, and visual ergonomics as important measures for reducing visual discomfort among digital-device users (Coles-Brennan et al., 2019; Kaur et al., 2022; Singh et al., 2022).

The significant association between seating position and computing devices showed that seating too close to computing devices was associated with higher odds of computer vision syndrome. This finding was consistent with recent evidence showing that ergonomic factors were associated with CVS among computer users (Dessie et al., 2018; Gasheya et al., 2024). The multivariable logistic regression analysis revealed that university affiliation was the only independent predictor of CVS after adjusting for confounding factors (aOR = 2.79, 95% CI: 1.27–6.11, p = 0.010). This finding suggests that the associations observed between CVS and other factors in the bivariate analysis, including working hours, use of computer glasses, eye examination, seating distance, and eye lubrication, may be partly explained by confounding. The stronger association observed among UITM lecturers compared with UPM lecturers may reflect differences in institutional teaching loads and screen-based task demands between teaching-oriented and research-oriented universities. These findings are consistent with previous evidence suggesting that institutional and organizational factors play an important role in shaping occupational health outcomes among university staff (Gasheya et al., 2024). The attenuation of other variables after adjustment underscores the importance of using multivariable methods to identify true independent predictors, rather than relying solely on bivariate analyses.

The use of eye lubrication was associated with CVS in this study, consistent with evidence suggesting that tear-film management may help reduce ocular discomfort among digital-device users. Recent reviews also indicated that dry eye is a common symptom of digital eye strain and that tear-film management may help reduce ocular discomfort among digital-device users (Coles-Brennan et al., 2019; Kaur et al., 2022; Singh et al., 2022). The exploratory machine-learning analysis generally supported the

findings from the conventional statistical analysis. University, working hours during COVID-19, seating distance from the computing device, use of eye lubrication, eye examination, and use of computer glasses were ranked among the leading predictors of CVS. These findings were broadly consistent with the chi-square analysis, in which university, working hours, seating distance, computer glasses, eye examination, and eye lubrication were significantly associated with CVS. However, the models demonstrated only moderate predictive performance (AUC = 0.70) with relatively low specificity, which is likely attributable to the small sample size and the high prevalence of CVS creating class imbalance. These findings should therefore be interpreted as exploratory rather than as evidence of strong predictive ability.

5. Conclusion

This study examined the prevalence of self-reported computer vision syndrome and its associations with sociodemographic characteristics, working characteristics, and working conditions among university lecturers during the COVID-19 pandemic in Malaysia. CVS was highly prevalent, affecting 77.6% of the respondents, coinciding with a marked increase in daily screen time during the pandemic. The most frequently reported symptoms were eye fatigue, headache, eye strain, and blurred vision. University affiliation was the only independent predictor of CVS after adjusting for confounding factors, with lecturers from UITM having approximately 2.8 times higher odds of CVS compared with those from UPM. Factors including the use of computer glasses, appropriate seating distance, eye lubrication, and regular eye examination were associated with CVS and should be considered in the development of occupational health programmes targeting university lecturers. Future studies with larger and more diverse samples, validated CVS instruments, and longitudinal designs are needed to establish causal relationships and to develop more robust predictive models.

6. Recommendation

Based on this study, lecturers should go for further eye check-up if the symptoms are prolonged. It is recommended to properly take care of the eyes and maintain healthy working conditions. The use of computer glasses, suitable seating position, eye lubrication, and eye examination were associated with CVS in this study and should be considered in occupational health programmes targeting university lecturers. More surveys and studies are needed on the prevalence of computer vision syndrome among lecturers, and future studies may also focus on industrial workers and administrative workers to fulfil the research gap and collect more data as a reference to plan further strategies to reduce the prevalence of computer vision syndrome among the workers during the COVID-19 pandemic.

7. Limitations

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design precludes causal inference. All associations reported in this study are observational, and it cannot be determined whether the identified factors preceded or resulted from CVS.

Second, CVS was defined as the presence of at least one self-reported symptom, which is a broad definition that may have overestimated the true prevalence of CVS. Future studies should consider using validated scoring instruments or more conservative case definitions that require symptoms to occur frequently or specifically during or after computer use. Third, the study relied entirely on self-reported symptoms without clinical examination, which may introduce recall bias and social desirability bias. Fourth, the sample was limited to lecturers from two Malaysian public universities, which limits the generalizability of the findings to other populations, occupational groups, or geographical settings. Fifth, the online distribution of the questionnaire may have introduced selection bias, as lecturers who were more engaged with digital platforms may have been more likely to respond. Sixth, while the internal consistency of the CVS symptom scale was satisfactory (Cronbach's α = 0.890), other psychometric properties such as test-retest reliability and construct validity were not formally evaluated in this study. Seventh, with 18 chi-square tests conducted, the possibility of type I error due to multiple comparisons cannot be excluded. However, the finding that university affiliation remained an independent predictor of CVS in the multivariable logistic regression analysis (aOR = 2.79, p = 0.010) provides additional support for this association beyond the bivariate analysis. Finally, the machine-learning analysis was exploratory due to the relatively small sample size (n = 174) and the high prevalence of CVS (77.6%), which created class imbalance and contributed to the low specificity observed across all three models. The sample size was insufficient to meet the recommended events-per-variable ratio for robust machine-learning model development, and the findings should not be interpreted as evidence of strong predictive ability.

Declarations

Ethics Approval

This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Ethic Committee For Research Involving Human Subject, Universiti Putra Malaysia (Reference No.: JKEUPM-2021-069).

Consent to Participate

Informed consent was obtained electronically from all participants prior to completing the online questionnaire. Participants were informed of the study objectives and their right to withdraw at any time.

Consent for Publication

Not applicable. This manuscript does not contain any individual person's identifiable data.

Clinical Trial Number

Not applicable.

Competing Interests

The authors declare no competing interests.

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Author Contribution

J.C. conceptualised the study, clean the data, performed the statistical and machine-learning analyses, and wrote the main manuscript text, prepard figure 1, table 6-9. L.H.M.J. assisted with data collection ,wrote and reviewed the manuscript, prepared table 1-5. I.R. supervised the study, provided critical revision of the manuscript for important intellectual content, and approved the final version for submission. All authors reviewed and approved the final manuscript.

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Availability of Data and Materials

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request. The data are not publicly available to protect the privacy and confidentiality of the participants.

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Figures

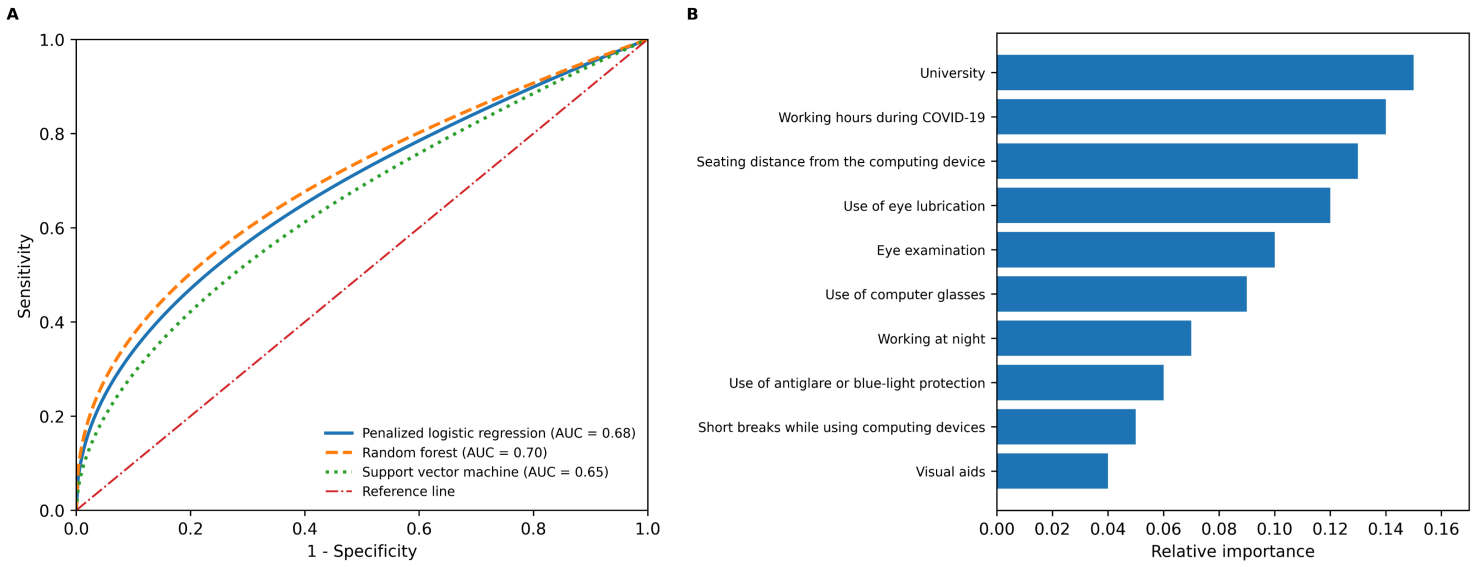


Figure 1

Machine-learning analysis for predicting computer vision syndrome. (A) Receiver operating characteristic curves of the penalized logistic regression, random forest, and support vector machine models. (B) Variable importance ranking from the random forest model.