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Development and Validation of the Online Victimization Scale: Confirmatory Factor Analysis and Composite Reliability

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Abstract

Online victimization is harmful actions directed at individuals or institutions through digital technology. This study aims to develop, validate, and examine the psychometric properties of the Online Victimization Scale (OVS). The researchers constructed and adapted several items from the Online Victimization Scale (OVS) by Tynes et al. (2014) and the Perceived Online Racism Scale (PORS) by Keum (2021), resulting in 54 items that were translated into Indonesian. A quantitative research method was employed using an accidental sampling technique. Data were collected from 204 individuals aged 14-23 years who were active social media users. Data analysis was conducted using Confirmatory Factor Analysis (CFA)to evaluate the factor structure. Score reliability was assessed by calculating composite omega and stratified alpha values using the lavaan package in R. The results indicated high inter-factor correlations, prompting a second-order factor analysis. The first-order and second-order models demonstrated good model fit indices with no significant differences, resulting in a final scale of 16 items. Measurement invariance testing using multi-group CFA confirmed that the scale met the criteria for scalar invariance, as indicated by minimal changes in ΔCFI and ΔTLI (<0.01). These findings validate the equivalence of the factor structure, factor loadings, and item intercepts between male and female participants, ensuring that score differences reflect actual differences in the online victimization construct rather than measurement bias.

Keywords: Confirmatory Factor Analysis, composite reliability, online victimization, adolescents and early adulthood

Abstrak

Viktimisasi daring mengacu pada tindakan merugikan yang ditujukan kepada individu atau institusi melalui teknologi digital. Penelitian ini bertujuan untuk mengembangkan, memvalidasi, dan mengkaji properti psikometrik dari Online Victimization Scale (OVS). Peneliti menyusun dan mengadaptasi sejumlah item dari Online Victimization Scale (OVS) oleh Tynes et al. (2014) dan Perceived Online Racism Scale (PORS) oleh Keum (2021), menghasilkan 54 item yang telah diterjemahkan ke dalam Bahasa Indonesia. Penelitian ini menggunakan metode kuantitatif dengan teknik accidental sampling. Data dikumpulkan dari 204 individu berusia 14–23 tahun yang merupakan pengguna aktif media sosial. Analisis data dilakukan menggunakan Confirmatory Factor Analysis (CFA) untuk mengevaluasi struktur faktor. Reliabilitas skor dievaluasi dengan menghitung nilai composite omega dan stratified alpha menggunakan paket lavaan dalam R. Hasil analisis menunjukkan adanya korelasi tinggi antarfaktor, sehingga dilakukan analisis faktor orde kedua. Baik model orde pertama maupun orde kedua menunjukkan indeks kecocokan model yang baik tanpa perbedaan yang signifikan, sehingga diperoleh skala akhir dengan 16 item. Pengujian measurement invariance menggunakan CFA multikelompok mengonfirmasi bahwa skala ini memenuhi kriteria scalar invariance, sebagaimana ditunjukkan oleh perubahan ΔCFI dan ΔTLI yang sangat kecil (<0,01). Temuan ini memvalidasi kesetaraan struktur faktor, factor loadings, dan item intercepts antara partisipan laki-laki dan perempuan, sehingga perbedaan skor mencerminkan perbedaan aktual dalam konstruk viktimisasi daring, bukan disebabkan oleh bias pengukuran.

***Kata kunci**: Confirmatory Factor Analysis, composite reliability, online victimization, remaja dan dewasa awal*

Introduction

The rapid advancement of technology has significantly transformed various aspects of life, including communication, shopping, and learning. Nowadays, nearly all activities are facilitated by technology, making daily tasks more manageable. Communication has become easier, information is more accessible, and activities such as time management and transportation are greatly enhanced. However, alongside these benefits, technology also brings negative consequences, such as addiction, cyberbullying, privacy violations, and other digital-related issues (Çavuş, 2023). These vulnerabilities can be exploited for fraud, crime, sexual victimization, and cyberbullying, posing serious risks to individuals in the digital world (Wati et al., 2023). People/internet users who have experienced the above or are victims of online bullying are called online victimization, according to Tynes & Giang (2009). This includes experiences such as cyberbullying, online harassment, exposure to unwanted sexual content, and online racial prejudice (Henson, 2012; Malaki, 2020). Research indicates that adolescents often face various forms of online crime, including sexual solicitation, exposure to sexual content, and harassment (Finkelhor et al., 2000). Furthermore, other studies have explored how different types of online victimization may lead to cyberbullying or sexting. (Nedelec et al., 2018).

The prevalence of online victimization in Indonesia has been steadily increasing, particularly among children and adolescents. Data from the Indonesian Child Protection Commission (KPAI) show a significant rise in cybercrimes against children, from 322 cases in 2014 to 679 cases in 2018, encompassing offences such as pornography, sexting, cyberbullying, online gambling, and fraud (KPAI, 2019, July 24). Moreover, children and adolescents also experience victimization on social media, including harassment, intimidation, and the unauthorized disclosure of their identities, further exacerbating their trauma (Maulida & Romdoni, 2024). The threat of online victimization extends beyond individuals and includes the spread of racist content, discriminatory comments that reinforce stereotypes, and biased digital algorithms that perpetuate racial discrimination. Additionally, biased representations of specific groups within digital content further distort public perception and reinforce societal prejudices (Al-Mujtahid et al., 2023).

The psychological impact of online victimization is profound, causing consequences such as loss of concentration, anger, retaliation, avoidance, depression, and even suicidal tendencies (Permatasari, 2022), Online dating scams have also been associated with changes in self-status and social standing (Wang, 2022). This is supported by other studies showing that loneliness and social anxiety predict increased vulnerability to online victimization (Eijnden et al., 2014).

Adolescents and young adults aged 14-23 years are often victims or perpetrators of online crimes, such as cyberbullying, due to their high use of social media (Zhu et al., 2021). For example, in Spain, 61% of adolescents reported experiencing online abuse during the past year in 2015, with 39.5% reporting sexual abuse and 53.4% reporting non-sexual abuse, while 31% experienced both types of abuse simultaneously (Montiel et al., 2016). Similarly, an estimated 36% of adolescents in Denmark were involved in online fraud or scams in 2022 (Kristiansen & Jensen, 2023).

In line with global trends, Indonesia has also witnessed a rise in online fraud and harmful digital content. Victims often hesitate to report due to intimidation by perpetrators, and detailed data on online victimization in Indonesia remains scarce. Meanwhile, the Indonesian Internet Service Providers Association (APJII) reported that approximately 210 million Indonesians, or 78.4% of the total population, were internet users in 2022 (APJII, 2022; Hapsari et al., 2023). Incidents of hacking, phishing, pornography, online fraud, and credit card theft are becoming increasingly prevalent. Although many cases of online victimization occur, valid and reliable assessment tools specific to Indonesia are still lacking.

While the frequency of victimization incidents can be measured, quantification alone is insufficient to capture the severity and psychological impact fully. Two individuals may experience the same number of incidents but with different intensities and consequences. Thus, a comprehensive measurement scale is crucial to understanding online victimization's true extent and informing effective intervention strategies.

Available online victimization assessment tools are primarily developed in foreign contexts and have not yet been adapted for use in Indonesia. Previous research abroad has developed various instruments, such as the Cyber Victimization Questionnaire (CYVIC) for adolescents (Álvarez-García et al., 2017), the Online Victimization Scale (Tynes et al., 2014) and the Cyber Victimization Emotional Impact Scale (Elipe et al., 2017). Other tools include multidimensional scales for peer bullying both online and offline (Sumter et al., 2015) and the Revised Cyber Bullying Inventory (RCBI) (Topcu & Erdur-Baker, 2010). Finally, the development of the measuring instrument "Online Victimizations Scale (OVS)" has four dimensions, namely general online victimization, sexual online victimization, Individual Online Racial Discrimination, and Vicarious Online Racial Discrimination (Tynes et al., 2014). The phenomenon of online victimization is quite common in Indonesia, but there is still very little development of the Online Victimization scale. San Miguel et al. (2020) highlighted the need to accurately measure online victimization to understand its patterns and associated risk factors better. Consequently, developing a robust measurement instrument is crucial to capturing victims' experiences comprehensively. Thus, this study aims to create a measuring instrument for online victimization in Indonesia using the theory of Tynes et al. (2014), which divides online victimization into four dimensions 1). General online victimization, 2). Sexual online victimization 3). Individual online racial discrimination 4). Vicarious online racial discrimination. This measuring instrument adopts items from OVS by Tynes et al. (2014) and PORS by Keum (2021), which are then translated into Indonesian and adjusted. The scale developed in this study differs from and offers advantagessss over previous scales, as Keum and Tynes' research did not include aspects of online fraud. Additionally, this scale has been adapted to the local cultural context in Indonesia. These adjustments were made by incorporating statement items that accurately reflect the nature of online victimization in Indonesia.

Methods

Participants

The procedure in this study involved 204 samples. This sample size was determined based on the reliable analysis of CFA, which included>200 samples (Wolf et al., 2013). Participants included adolescents and early adults in the age range of 14-23 years. The average age is 18 years, with a standard deviation of 3. In this study, the participants involved based on gender include 70 (34%) male participants and 134 (66%) female participants. Regarding educational status, there are 53 (26%) participants from Junior High School, 44 (22%) from Senior High School, and 107 (52%) from Higher Education. The following are the demographic distributions.

Table 1. Participant Demographic

	N	%
Gender		
Female	134	66%
Male	70	34%
Education Level		
Higher Education	107	52%
Senior High School	44	26%
Junior High School	53	22%
Total	204	100%

Source: Personal data (2024).

Instruments

This study developed the Online Victimization Scale by adopting the four-factor model proposed by Tynes et al. (2014). These dimensions classify online victimization into four categories which included (a) general online victimization, which includes personal victimization, harassment, appearance-based victimization, and negative comments; (b) Sexual Online Victimization, which focuses on experiences of sexual victimization, such as being asked to send sexual images or being involved in unwanted sexual discussions online, this assesses the individual's experience of sexual victimization experienced directly by the individual. (c) Individual Online Racial Discrimination refers to direct experiences of racial discrimination online, including malicious or abusive comments targeting an individual's race or ethnicity. This includes instances where individuals face malicious or abusive comments online because of their race or ethnic background. (d) Vicarious Online Racial Discrimination is the experience of witnessing or being exposed to racial discrimination against others online, such as encountering derogatory jokes or comments about people of a particular race or ethnic group.

In this study, the researcher employed the instrument adaptation procedure developed by Beaton et al. (2000) to ensure the measurement tool's conceptual, semantic, and cultural equivalence. This process involved an English language lecturer, a psychology practitioner, a psychologist, a psychology lecturer, and a psychology student proficient in both the source and target languages. The adaptation followed five main stages.

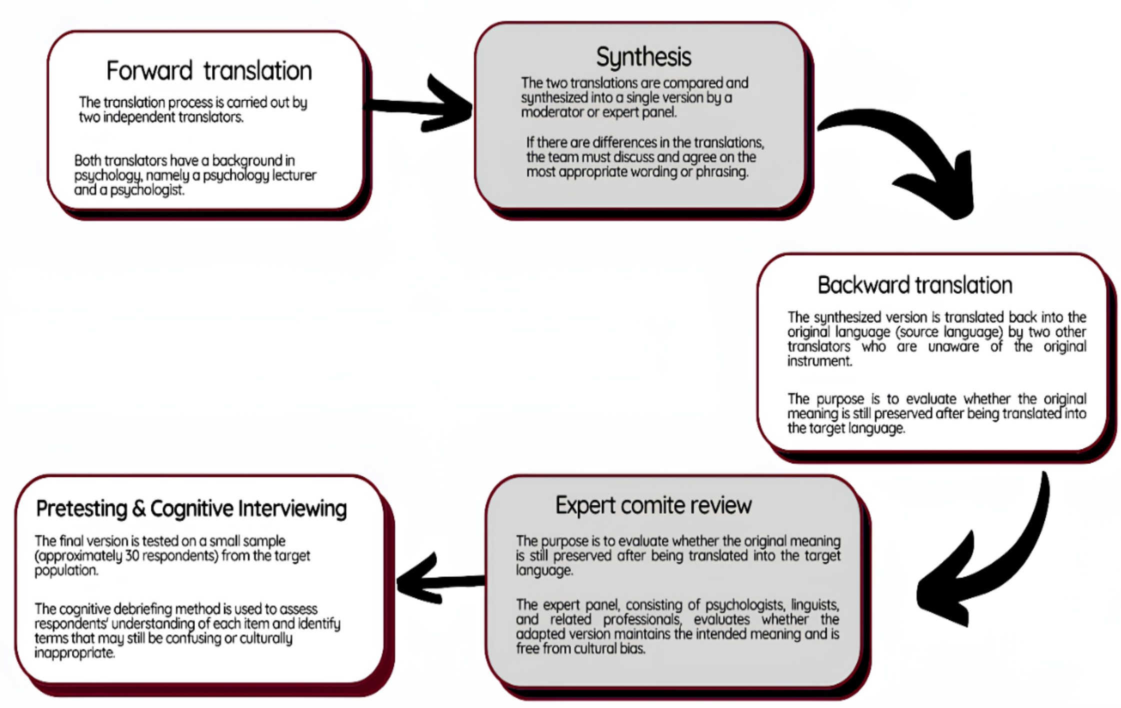
The first stage was forward translation, where two independent translators, namely an English language lecturer and a psychology practitioner, translated the instrument from the source language to the target language separately to ensure accuracy in psychological and linguistic terminology.

The second stage was translation synthesis, in which the two translated versions were compared and synthesized into a single final version through discussion to agree on the most appropriate terminology.

The third stage was the back translation, where two other translators, a psychology student proficient in both languages and a psychology lecturer, translated the instrument back into the source language without prior knowledge of the original version. This step aimed to preserve the original meaning after the translation process.

The fourth stage was the expert panel review, which comprised all the experts involved in this process. They assessed the translated instrument's conceptual, semantic, and cultural appropriateness and identified inaccurate or potentially culturally biased terms. Revisions were made based on the panel discussion if any discrepancies were found.

The fifth stage was pretesting, in which the final version of the instrument was tested on a small group of respondents using an open-ended questionnaire method. Respondents were asked to provide feedback on the clarity of the language and the ease of understanding each item. Additionally, they were asked to rate their level of comprehension and suggest possible improvements if necessary. The collected responses were analyzed to identify any issues, and further revisions were made before the instrument was used in the main study.



Source: Beaton et al. (2000)

Figure 1. Procedures for Cross-Cultural Adaptation

Several items were adapted from previously validated instruments. For example, an item from Tynes et al. (2014) reads: "People have posted mean or rude things about me on the internet," translated as "Orang-orang memposting hal-hal jahat atau kasar tentang saya di internet." Another item from Keum (2021) states: "Seen other racial/minority users being treated like a second-class citizen," translated as "Di sosial media saya melihat pengguna ras/minoritas lain diperlakukan seperti warga negara kelas dua." All adapted items were reviewed by English and Indonesian language experts to ensure semantic equivalence.

Table 2. Blueprint Online Victimization Scale

Dimensions	Item Number	Total	Per cent
General Online Victimization (GOV)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,13, 14, 15, 16, 17, 18, 19, 20	20	37,04%
Sexual online Victimization (SOV)	21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32	12	22.22%
Individual Online Racial (IORD)	33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43	11	20.37%
Vicarious Online Racial Discrimination (VORD)	44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54	11	20.37%
Jumlah Total		**54**	**100%**

Source: Personal data (2024).

Of the 54 items developed, 37.04% belong to the *General Online Victimization* (GOV) dimension, 22.22% to *Sexual Online Victimization* (SOV), 20.37% to *Individual Online Racial Discrimination* (IORD), and 20.37% to *Vicarious Online Racial Discrimination* (VORD). This proportion reflects the conceptual scope and relevance of each dimension, with GOV having the largest share because it encompasses more general forms of online victimization, thus requiring more items to capture the diversity of victimization experiences. The complete blueprint is presented in Table 2.

Data Collection

The sampling technique uses incidental sampling, where the selection is not determined from the start, but the sample is a person who happens to be encountered by the research criteria (Sugiyono, 2012; Amin et al., 2023). Data was collected using two methods, the Clerical method or paper and pencil, in 2 schools, MAN 3 Cirebon and MTs AI Mertapada. The second is done online using Google Forms, distributed on social media platforms such as WhatsApp, Twitter, and Discord. Data collection activities were conducted for approximately two months, from February to April.

Data Analysis

The researcher conducted construct validity using confirmatory factor analysis (CFA) to find out the fit model of the proposed measurement. The index determining the fit model uses statistical tests like the Chi-Square test. However, the Chi-Square test is susceptible to the number of samples; if the sample is large, it will tend to be significant, meaning the model does not fit (Iacobucci, 2010). So, alternatives can be referred to as indices such as GFI, RMSEA, CFI, and TLI to see if the difference between the two correlation matrices is statistically significant. With GFI X2/df < 3.00, GFI > 90 (Byrne, 2024). AGFI > 0.80 (Lee & Lai, 2021) CFI > 0.95 good fit, 0.90 traditional, > 80 lousy fit. RMSEA < 0.05 good fit, 0.05-1.0 traditional, and > 1.0 lousy fit. TLI> 0.95 is in the good fit category or has a good fit model (Hu & Bentler, 1999). In this study, the statistical software used is R programming language with the Lavaan package. If, after analysis, the model does not fit, the next step can be a model modification, such as freeing the correlation between measurement errors or dropping inappropriate variables (Umar & Nisa, 2020). Still, the researcher chooses to drop items with low factor loading or factor eyes and high inter-item error correlations.

Composite reliability is used to evaluate its reliability, namely, omega reliability. Composite reliability is used when modelling and assessing how reliable a particular concept is (Peterson & Kim, 2013). According to Geldof, the formula used to measure composite reliability involves the factor loading value of each indicator that makes up the instrument (λ) and the error-index value of each indicator (δ) (Retnawati, 2017). A good CR or Construct Reliability value is> 0.70 (Yusuf & Sartika, 2021). Then, the discriminant validity test is carried out, namely the average variance extracted (AVE). Average Variance Extracted, or AVE, helps measure the validity of the construct. AVE compares the variation obtained from a construct with the variation arising from measurement error (Santos & Cirillo, 2023). The AVE acceptance limit is> 0.5.

The purpose of this study is to examine whether the instrument used demonstrates equivalent measurement capability (measurement invariance) across different groups based explicitly on gender (female and male) (Jamaludin, 2019). Testing for measurement invariance is crucial to ensure that the differences between groups reflect actual differences in the measured construct rather than biases introduced by differences in how the instrument functions across groups (Putnick & Bornstein, 2016). The study employed Multi-group Confirmatory Factor Analysis (MGCFA) to address this objective. MGCFA is a statistical approach within confirmatory factor analysis that examines whether the same latent measurement model applies consistently across multiple groups. This method enables the evaluation of equivalence at various levels of measurement, including the relationship patterns between indicators, factor loadings, and intercepts across groups (Kline, 2015).

Measurement invariance refers to the extent to which a measurement instrument yields conceptually equivalent results when applied to different groups. An instrument is considered invariant if the meaning of the construct it measures remains consistent across groups, allowing for valid and fair comparisons of scores (Chen, 2007). In this study, measurement invariance was evaluated across three primary levels. The first stage is configural invariance, which examines whether the basic factor structure of the instrument is consistent across groups without imposing parameter constraints. If achieved, it indicates that the pattern of relationships between indicators and latent factors is similar across groups. Next, metric invariance tests the equality of factor loadings across groups. If supported, it means that the strength of the relationships between indicators and latent factors is equivalent, allowing for valid comparisons. The final stage is scalar invariance, which assesses the equality of intercepts across groups. If established, it ensures that the baseline values of the scale are the same, enabling valid comparisons of latent means.

Results

Normality

Based on the descriptive analysis results in Table 3, item mean scores range from 1.52 to 3.45, indicating variation in respondents' tendencies across items. The standard deviation (SD) values range from 0.67 to 1.59, reflecting relatively low dispersion and suggesting a moderate level of response homogeneity.Skewness values range from –0.58 to 1.59, with most items exhibiting negative skewness, indicating a left-skewed distribution (i.e., a tendency toward higher response values). Kurtosis values range from –1.58 to 3.19, where most are negative or close to zero, suggesting that the distributions are generally normal or slightly platykurtic. However, a few items show higher positive kurtosis, indicating more peaked distributions.

Given that the overall item distributions approximate normality, Maximum Likelihood Estimation (MLE) was used in the Confirmatory Factor Analysis (CFA), as it assumes multivariate normality in the data for optimal parameter estimation.

Table 3. Descriptive Statistics

Item	Mean	SD	Skewness	Kurtosis	Item	Mean	SD	Skewness	Kurtosis
GOV1	1.96	0.979	0.884	0.236	SOV8	1.58	0.768	1.202	1.200
GOV2	3.19	1.497	-0.269	-1.373	SOV9	1.52	0.669	0.924	-0.309
GOV3	3.03	1.533	-0.224	-1.529	SOV10	1.63	0.793	1.309	2.051
GOV4	3.18	1.531	-0.284	-1.439	SOV11	1.55	0.696	0.955	0.001
GOV5	3.33	1.392	-0.426	-1.111	SOV12	1.88	0.941	1.070	1.003
GOV6	3.33	1.447	-0.441	-1.195	IORD1	2.57	1.179	-0.130	-1.351
GOV7	3.40	1.430	-0.582	-1.033	IORD2	2.65	1.154	-0.260	-1.236
GOV8	3.45	1.470	-0.551	-1.127	IORD3	2.62	1.145	-0.243	-1.292
GOV9	3.23	1.505	-0.311	-1.400	IORD4	2.58	1.219	-0.118	-1.453
GOV10	3.21	1.517	-0.337	-1.391	IORD5	2.54	1.221	-0.075	-1.465
GOV11	3.17	1.507	-0.322	-1.395	IORD6	2.46	1.196	0.018	-1.415
GOV12	3.09	1.592	-0.213	-1.575	IORD7	2.52	1.181	-0.102	-1.429
GOV13	3.17	1.453	-0.294	-1.345	IORD8	2.60	1.189	-0.079	-1.275
GOV14	3.06	1.537	-0.223	-1.501	IORD9	2.57	1.166	-0.177	-1.373
GOV15	3.06	1.557	-0.186	-1.542	IORD10	2.57	1.14	-0.193	-1.303
GOV16	3.18	1.537	-0.275	-1.454	IORD11	2.52	1.138	-0.150	-1.322
GOV17	3.12	1.445	-0.295	-1.318	VORD1	2.81	1.181	-0.250	-1.035
GOV18	3.14	1.591	-0.242	-1.552	VORD2	2.82	1.122	-0.217	-1.002
GOV19	3.31	1.418	-0.381	-1.202	VORD3	2.85	1.122	-0.298	-0.865
GOV20	3.20	1.557	-0.268	-1.476	VORD4	2.58	1.127	-0.176	-1.348
SOV1	2.00	0.891	0.517	-0.186	VORD5	2.61	1.179	-0.100	-1.244
SOV2	1.84	0.946	1.140	0.959	VORD6	2.81	1.181	-0.250	-1.035
SOV3	1.64	0.766	1.321	2.163	VORD7	2.60	1.189	-0.031	-1.229
SOV4	1.62	0.806	1.247	1.308	VORD8	2.68	1.162	-0.134	-1.211
SOV5	1.64	0.785	1.171	1.266	VORD9	2.60	1.197	-0.121	-1.402
SOV6	1.55	0.731	1.089	0.283	VORD10	2.80	1.125	-0.205	-0.915
SOV7	1.63	0.824	1.589	3.190	VORD11	2.99	1.114	-0.412	-0.808

Source: Personal data (2024).

Content Validity

The content validity of the instrument was assessed by 11 expert raters, who evaluated six key aspects: (1) the alignment of items with the measured domain, (2) clarity and lack of ambiguity in item formulation, (3) ease of comprehension for the target respondents, (4) appropriateness of the response scale for measuring the items, (5) suitability of the underlying theoretical framework, and (6) overall suitability of the instrument for use.

The evaluation results indicated that the majority of experts agreed that the items were well-aligned with the intended domain and theoretical framework and appropriate for practical application. However, some discrepancies emerged regarding item clarity and formulation. Specifically, R3, R6, and R7 identified ambiguities in certain items, while R6 expressed concerns about domain alignment. Despite these variations, all raters unanimously agreed that the instrument was appropriate for use, indicating strong overall content validity. These findings suggest that while minor revisions may be necessary to enhance item clarity, the instrument is fundamentally sound and suitable for further empirical validation.

Table 4. Content Validity

Raters	Are all items aligned with the domain measured?	Are the items clearly formulated without ambiguity?	Is the language easy to understand for the target respondents?	Is the rating or response scale appropriate for measuring the items?	Is the theory used appropri ate?	Is this instrument suitable for use?
R1	Yes	Yes	Yes	Yes	Yes	Yes
R2	Yes	Yes	Yes	Yes	Yes	Yes
R3	Yes	No	Yes	Yes	Yes	Yes
R4	Yes	Yes	Yes	Yes	Yes	Yes
R5	Yes	Yes	Yes	Yes	Yes	Yes
R6	No	No	Yes	Yes	Yes	Yes
R7	Yes	No	Yes	Yes	Yes	Yes
R8	Yes	Yes	Yes	Yes	Yes	Yes
R9	Yes	Yes	Yes	Yes	Yes	Yes
R10	Yes	Yes	Yes	Yes	Yes	Yes
R11	Yes	Yes	Yes	Yes	Yes	Yes

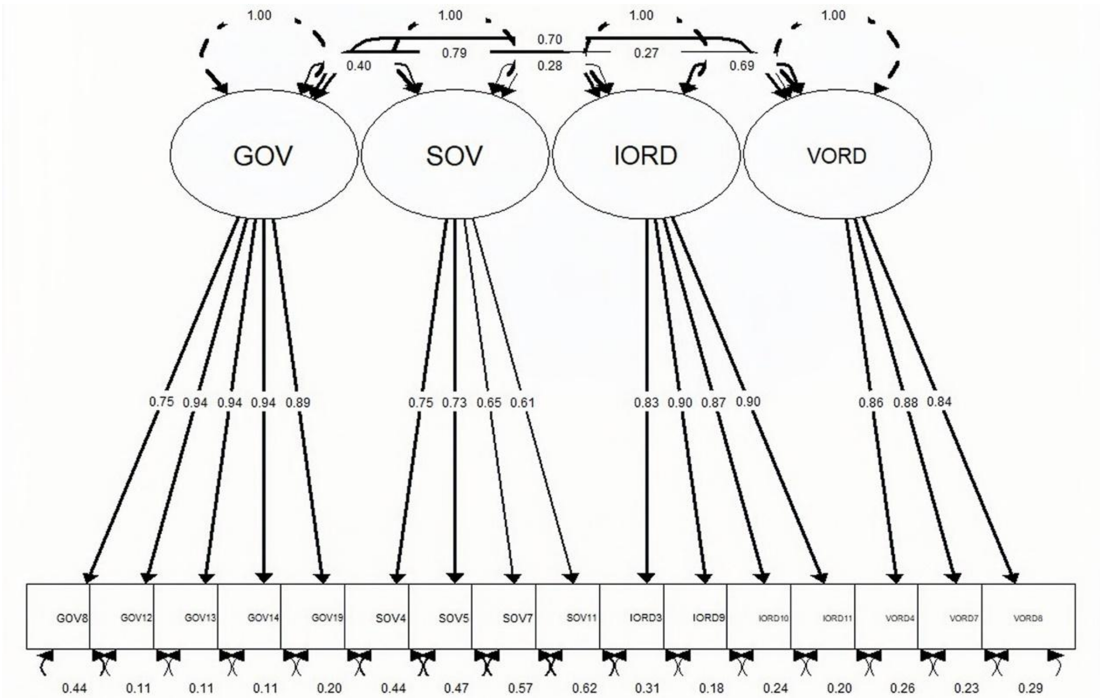
Source: Personal data (2024).

Initially, 12 experts participated in the content validity assessment. However, after conducting a psychometric analysis of the score distribution using Z-scores, Mean Absolute Deviation (MAD), and Winsorization, it was found that one rater was a significant outlier, consistently assigning scores much lower than the other raters. The Z-score for this rater was -2.72, indicating extreme deviation from the mean, and the MAD for this rater was 95.58, which was significantly higher than the overall MAD of 26.22, further reinforcing the presence of an unusual rating pattern. After applying Winsorization adjustments, the rater's score increased by +56.6 points. Therefore, this rater was excluded from the analysis to improve interrater reliability and content validity.

The items excluded at this stage were GOV7 = 0.64, GOV8 = 0.64, SOV8 = 0.64, GOV10 = 0.67, GOV19 = 0.67, IORD9 = 0.67, and IORD11 = 0.67. These values refer to Aiken's V coefficients when rated by 12 experts. After excluding the outlier, the item validity analysis was repeated using Aiken's V. The revised results showed V values ranging from 0.70 to 0.88, with an average of 0.78. According to Aiken's V table for 11 raters with a 5% significance level and a five-point rating scale, the minimum validity threshold was 0.70. Therefore, all remaining items met the validity criteria and were retained for subsequent analysis.

First-order confirmatory factor analysis

From the analysis using first-order CFA on the initial model, it was found that the model did not fit with the following fit indices χ^2= 2665.480, df = 1319, Probability = 0.000, RMSEA = 0.071, SRMR = 0.095, GFI = 0.672, AGFI = 0.640, TLI = 0.887, CFI = 0.894. The researcher then performed a modification index by correlating the residuals of each item and subsequently eliminated items with high residual correlations. This resulted in 16 remaining items. This model is shown in Figure 1 below.



Source: Personal data (2024).

Figure 2. First-order Model

The analysis found that the four-factor model on OVS has a good model fit index, with χ^2 =104.662, df = 98, Probability = 0.304, RMSEA = 0.018, SRMR = 0.035, GFI = 0.940, AGFI = 0.916, CFI = 0.998, TLI = 0.997. However, the OVS four-factor model indicated a reasonably high correlation between factors:

Table 5. Correlation between Factors

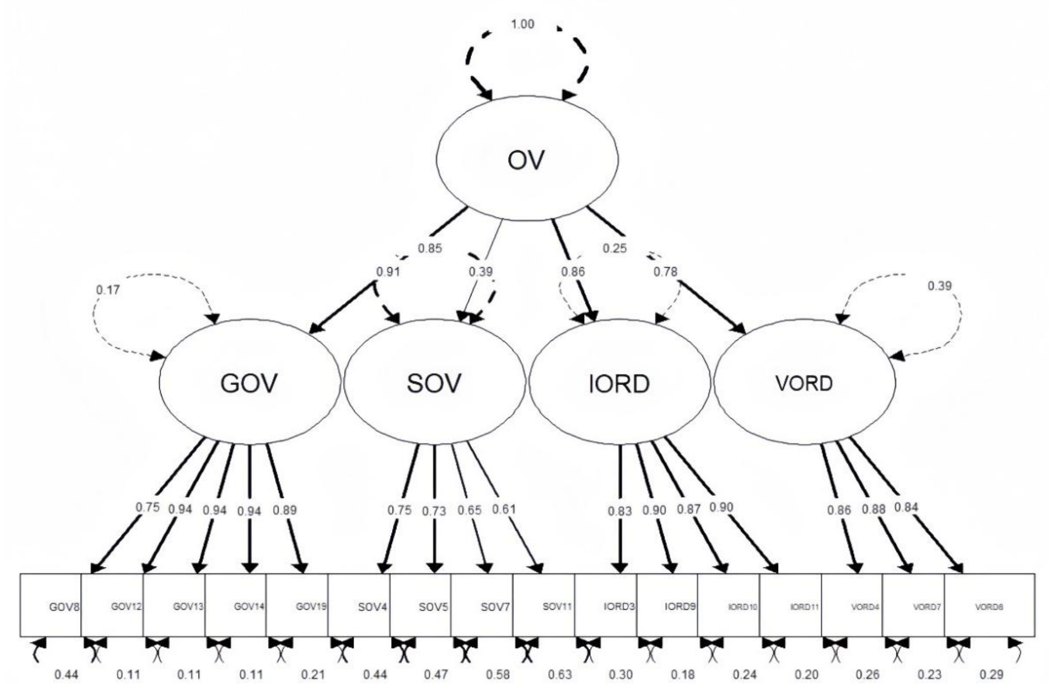
Dimensions	1	2	3	4
GOV	1	0.396	0.787	0.704
SOV		1	0.281	0.269
IORD			1	0.690
VORD				1

Source: Personal data (2024).

Table 5 shows that the correlation between GOV and SOV is 0.39, between GOV and IORD is 0.787, and between GOV and VORD is 0.704. Additionally, the correlation between SOV and IORD is 0.281, between SOV and VORD is 0.269, and between IORD and VORD is 0.690, which is a high correlation. This could potentially lead to further testing using a second-order model. The second-order model accounts for the correlation between first-order factors in model accuracy testing (Brown, 2015). According to Brown, the main reason for conducting further CFA testing with the second-order model is because each factor has a high correlation. This suggests that the first-order factors may be subdimensions of one larger dimension. In this study, the cause of conducting advanced tests (Ampuni & Buwono, 2022).

Second-order confirmatory factor analysis

Before the second-order analysis, model identification testing is done to identify an overidentified model (Brown, 2015; Byrne, 2012). After identifying the model, it was found that the second-order model with four factors is overidentified, with a sample moment of 136 and the number of estimated parameters being 36, where the sample moment exceeds the number of estimated parameters. The next step is to test the model according to the analysis results.



Source: Personal data (2024).

Figure 3. Second-order Model

The second-order model with four factors in OVS shows a good model fit, with χ^2= 108.626, Probability = 0.261, df = 100, RMSEA = 0.021, GFI = 0.938, AGFI = 0.915, TLI = 0.996, CFI = 0.997. To evaluate the suitability of the second-order model in more depth (Brown, 2015) recommends reviewing the magnitude of the second-order factor weights against each first-order factor and the first-order factors that the second-order factors can explain. The higher the factor weight score, the better the model. The results suggested a strong relationship between online victimization as a second-order factor with GOV (γ = 0.91), SOV (γ = 0.39), IORD (γ = 0.86), and VORD (γ = 0.78).

Model Comparison

After obtaining the fit model from the two models above, the next step is to compare the two models. This aims to determine which model is the most fitting or suitable for OVS. The first model is a first-order model where the four factors, namely GOV, SOV, IORD, and VORD, stand-alone. The second model involves four factors, GOV, SOV, IORD, and VORD, into online victimization sub-factors. The following is the model fit index of the two OVS models.

Table 6. Model Fit Index

Model	**Model Fit Index**							
	χ^2	χ^2/df	P-value	RMSEA	GFI	AGFI	TLI	CFI
Model 1	104.662	1.068	0.304	0.018	0.940	0.916	0.997	0.998
Model 2	108.626	1.086	0.261	0.021	0.938	0.915	0.996	0.997

Source: Personal data (2024).

To evaluate the factor structure of the Online Victimization Scale (OVS), a comparison was conducted between the first-order and second-order CFA models. The first-order model assumes that the four factors GOV, SOV, IORD, and VORD are independent but correlated with each other. In contrast, the second-order model assumes that these four factors are governed by a higher-order general factor, namely Online Victimization as the second-order factor.

The analysis results indicate that both models exhibit good fit, with similar fit indices. The first-order model yielded $\chi^2(104) = 104.662$, $p = 0.304$, RMSEA = 0.018, GFI = 0.940, AGFI = 0.916, TLI = 0.997, and CFI = 0.998, while the second-order model produced $\chi^2(100) = 108.626$, $p = 0.261$, RMSEA = 0.021, GFI = 0.938, AGFI = 0.915, TLI = 0.996, and CFI = 0.997. There is no significant difference in model fit between the two models, indicating that both the first-order and second-order models can adequately represent the factor structure of OVS.

An important step after model estimation in Confirmatory Factor Analysis (CFA) is evaluating the significance of each item in measuring the intended factor. After model estimation in Confirmatory Factor Analysis (CFA), the next important step is to evaluate the significance of each item in measuring the intended factor, which can be observed through the factor loading values. In analyses with small sample sizes, a factor loading greater than 0.5 and positive meets the necessary significance criteria to ensure an adequate relationship between the item and the measured factor (Hair et al., 2010). In the next step, the researcher analyses the first-order model with the justification that this model aligns better with the existing theoretical framework. Additionally, the SOV variable (one of the variables in the model) shows low correlation and γ (Gamma), which supports the choice of the first-order model. Subsequently, a significance test is conducted by examining the z-value of each item. If the z-value is less than 1.96, the item is considered insignificant and should be removed or revised to ensure the validity of the measurement model.

Table 7. First-order Factor Loading Item

Item	Estimate	SE	z-value	P(>|z|)
GOV8	0.746	0.072	6.22	P<0.001
GOV12	0.943	0.092	6.671	P<0.001
GOV13	0.944	0.084	6.672	P<0.001
GOV14	0.941	0.088	6.668	P<0.001
GOV19	0.891	0.078	6.575	P<0.001
SOV4	0.751	0.052	10.686	P<0.001
SOV5	0.728	0.051	10.33	P<0.001
SOV7	0.651	0.054	9.109	P<0.001
SOV11	0.612	0.046	8.482	P<0.001
IORD3	0.835	0.054	8.912	P<0.001
IORD9	0.904	0.057	9.304	P<0.001
IORD10	0.872	0.055	9.136	P<0.001
IORD11	0.896	0.055	9.262	P<0.001
VORD4	0.862	0.053	11.536	P<0.001
VORD7	0.876	0.056	11.684	P<0.001
VORD8	0.844	0.054	11.333	P<0.001

Source: Personal data (2024).

Table 7 shows that the factor loading is> 0.5 with a range of 0.613 - 0.944, and the z-value for the factor loading of the remaining 16 items is significant because the z-value is> 1.96. So, it can be concluded that the 16 items are valid for measuring the factors that have been determined.

Measurement Invariance Across Gender

Table 8. Results of Measurement Invariance

Model	χ²	Df	CFI	TLI	RMSEA	Δχ²	Δdf	p	ΔCFI	ΔTLI
Configural	238.437	196	0.985	0.981	0.046	-	-	-	-	-
Metric	257.158	208	0.982	0.979	0.048	18.721	12	0.093	-0.003	-0.002
Scalar	279.594	220	0.978	0.976	0.052	22.436	12	0.033	-0.004	-0.003

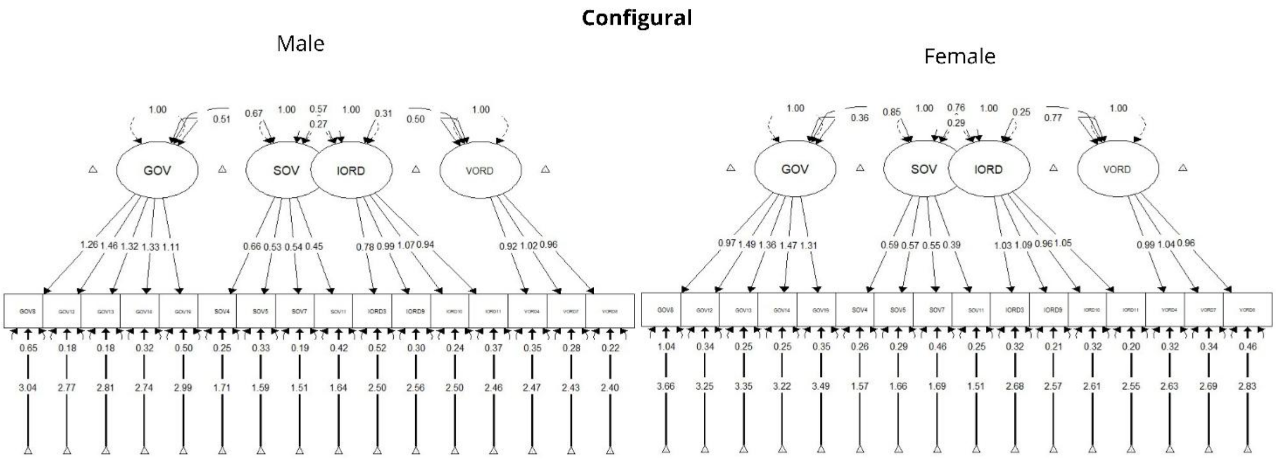
Source: Personal data (2024).

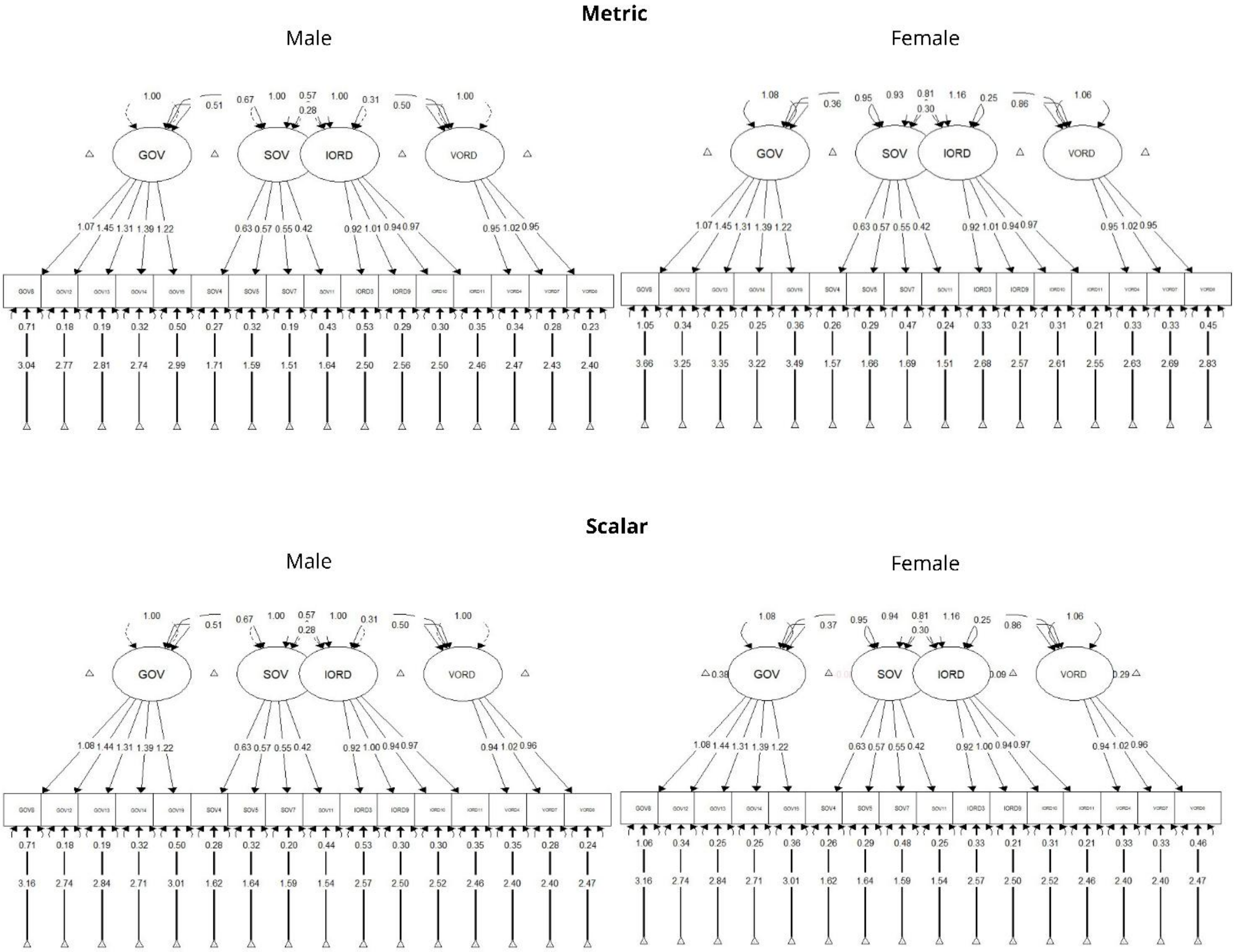
The MGCFA analysis was conducted to examine measurement invariance across two groups based on gender (male and female). The baseline model (i.e., configural invariance) was used as a starting point to test whether the hypothesized factor structure fits both groups. The results indicated that the configural invariance model fit the data well ($\chi^2 = 238.437$, df = 196, RMSEA = 0.046, CFI = 0.985, TLI = 0.981).

Next, the metric invariance model was tested by adding constraints on the factor loadings to be equal across the two groups. The analysis showed that the fit difference between the configural and metric invariance models was insignificant ($\Delta\chi^2 = 18.721$, $\Delta df = 12$, $p = 0.093$). Fit indices, such as ΔCFI (-0.003) and ΔTLI (-0.002), also showed tiny changes (less than 0.01), indicating that the factor loadings could be considered equivalent across groups.

Subsequently, the scalar invariance model was tested by adding constraints on the intercepts to be equal across the two groups. The results showed a slight decrease in model fit compared to the metric invariance model ($\Delta\chi^2 = 22.436$, $\Delta df = 12$, $p = 0.033$). Nevertheless, ΔCFI (-0.004) and ΔTLI (-0.003) values remained within acceptable limits (< 0.01), indicating that the intercepts could also be considered equivalent across groups. These results support scalar invariance, meaning that the factor structure, loadings, and intercepts can be considered equivalent between male and female groups.

Item parameters are presented in Figure 4. The analysis results indicate that, in the configural model, the unstandardized factor loadings for the male group ranged from 0.45 to 1.46, with intercept values between 1.51 and 3.04. In contrast, the unstandardized factor loadings for the female group ranged from 0.39 to 1.49, and intercept values ranged from 1.51 to 3.66. In the metric model, constraints were applied to the unstandardized factor loadings, equating the loading values across groups, which resulted in a range from 0.42 to 1.45. Since intercepts were not constrained in this model, they remained consistent with those in the configural model. Subsequently, constraints were imposed on both the factor loadings and intercepts in the scalar model, yielding unstandardized factor loadings ranging from 0.42 to 1.44 and intercepts ranging from 1.54 to 3.16. These findings suggest that the factor structure is relatively consistent across gender groups, supporting the assumption of measurement invariance across genders.





Source: Personal data (2024)

Figure 4. Multi-group Confirmatory Factor Analysis

Reliability

After conducting the validity test, the next step is to test the items' consistency, commonly called the reliability test. The reliability test uses the internal consistency method using stratified alpha and omega composite reliability. The results of the reliability test are shown in Table 3 below.

Table 9. Reliability

Dimensions	**CR**	**AVE**	**Stratified Alpha**	
General Online Victimization	0.945	0.80	0.951	0.990
Sexual Online Victimization	0.781	0.47	0.779	
Individual Online Racial Discrimination	0.93	0.77	0.93	
Vicarious Online Racial Discrimination	0.90	0.74	0.895	

Source: Personal data (2024).

Table 9 shows that the items on this scale are reliable, as evidenced by the results of the omega composite coefficient and the stratified alpha coefficient, which are> 0.70, and discriminant validity shown in the average variance extracted (AVE) is> 0.50. However, in the dimension of sexual online victimization, the average variance extracted (AVE) value = 0.47, which is <0.5. However, if the CR value is> 0.7 but the AVE <0.5 is still acceptable (Fornell & Larcker, 1981).

Discussion

The analysis began by testing the initial model using a first-order confirmatory factor analysis (CFA) approach. The preliminary results indicated that the model did not meet the recommended fit criteria. Consequently, model modifications were undertaken by allowing correlated error terms and eliminating items that exhibited more than three error correlations. Following these procedures, 16 valid items were retained.

After the modifications, the first-order model demonstrated a significant improvement in model fit indices, reflected in a low RMSEA value and high GFI, AGFI, TLI, and CFI values. These results indicate that the model achieved a good fit. However, the analysis also revealed relatively high correlations among the factors in the first-order model, which generally suggests the possibility of unidimensionality.

A second-order model was tested to evaluate a more parsimonious structure. Although the second-order model also demonstrated an acceptable fit, the changes in fit indices were relatively minor and statistically insignificant compared to the first-order model. This suggests that both models provide a structurally similar representation of the data.

Nonetheless, the researchers opted to retain the multidimensional approach not solely based on the high inter-factor correlations but also due to additional empirical evidence supporting the distinctiveness of the dimensions. In particular, the SOV dimension showed lower correlation and gamma values than the other dimensions, indicating a weaker contribution to the overall construct and reinforcing the argument that each dimension possesses unique characteristics.

This approach aligns with the findings and theoretical stance of Tynes et al. (2014), who, during the development of the original scale, also observed high inter-factor correlations in their first-order CFA. Nevertheless, they treated the dimensions as independent constructs, as each reflected different aspects of online victimization experiences, both conceptually and contextually.

However, the Sexual Online Victimization (SOV) dimension demonstrates a composite reliability (CR) of 0.781 with an average variance extracted (AVE) of 0.47. While the CR exceeds the 0.7 threshold, an AVE below 0.5 suggests that this dimension does not fully explain the variance in its indicators. A low AVE may indicate issues with convergent validity, though a high CR still reflects acceptable internal consistency. Revising the indicators within this dimension could help improve AVE and ensure alignment with the measured construct (Fornell & Larcker, 1981). Meanwhile, the Vicarious Online Racial Discrimination (VORD) dimension demonstrates a CR of 0.90 and an AVE of 0.74, with a stratified alpha of 0.895, indicating good validity and reliability, though there is room for improvement in internal consistency. Overall, the OVS scale exhibits good validity and reliability across most dimensions, with General Online Victimization and Individual Online Racial Discrimination standing out as dimensions with strong psychometric performance, while the Sexual Online Victimization dimension requires further refinement.

The General Online Victimization (GOV) dimension measures experiences of personal victimization, online harassment, appearance-related victimization, and negative comments on the internet. This dimension consists of five items, including experiences of reluctance to express opinions due to fear of online attacks, being a victim of identity theft, experiencing online harassment, receiving harsh or rude comments on the internet, and facing pressure in online groups such as WhatsApp. Based on the remaining items, this dimension is more closely related to personal victimization and negative comments from online users, whereas online sexual harassment is primarily categorized under the Sexual Online Victimization (SOV) dimension.

The Sexual Online Victimization (SOV) dimension measures online sexual harassment, including explicit images and conversations leading to unwanted sexual advances. This dimension consists of four items such as experiences of being pressured to send explicit photos or videos, being asked about sexual history by acquaintances, receiving inappropriate video chat requests from strangers, and receiving lewd comments on personal posts. The remaining items indicate that this dimension accurately reflects online sexual harassment, which primarily occurs in private online spaces. However, the correlation between this dimension and other factors in the CFA model tends to be lower, suggesting that the nature of online sexual victimization is more distinct compared to other forms of online victimization.

The Individual Online Racial Discrimination (IORD) dimension measures individual experiences of racial and ethnic discrimination online. This dimension consists of four items, including experiences of being perceived as provincial when using a local language on social media, being harassed by users initiating racist arguments without reason, receiving racial slurs based on online profiles, and being mocked for one's accent. These four items capture the essence of online racial discrimination at an individual level.

The final dimension, Vicarious Online Racial Discrimination (VORD), shares similarities with IORD but from a third-person perspective, observing online racial discrimination experienced by others. This dimension includes three items describing experiences, such as witnessing videos that discredit certain racial or ethnic groups, seeing threats of violence against racial minorities on social media, and observing minority users being treated as second-class citizens.

A high stratified alpha value (0.99) indicates excellent score reliability, meaning that the scores produced by the scale are internally consistent and contain minimal measurement error. This provides confidence that the scale can generate stable and dependable scores in measuring the intended construct.

At the next stage, measurement invariance testing on the Online Victimisation scale based on gender revealed no significant differences between males and females, with the analysis results supporting invariance up to the scalar level. This indicates that the factor structure, factor loadings, and intercepts can be considered equivalent, meaning the scale measures the construct of online victimization consistently across both groups. These findings align with the principle that scalar invariance ensures psychological constructs are measured without measurement bias, allowing for valid group comparisons (Byrne, 2012; Cheung & Rensvold, 2002). Support for scalar invariance further confirms that the score differences reflect actual differences in the measured construct rather than differences in item interpretation (Meredith, 1993). Thus, this scale is suitable for cross-group analysis without gender bias, as indicated by the small changes in fit indices such as ΔCFI and ΔTLI (<0.01) (Chen, 2007; Putnick & Bornstein, 2016; Schoot & Lugtig, 2012).

Although the second-order CFA model demonstrated a good fit to the data, several limitations of this study warrant attention. One of the primary concerns lies in the low correlations between the Sexual Online Victimization (SOV) dimension and the other factors and the low gamma coefficient for this dimension. Furthermore, the Average Variance Extracted (AVE) value for the SOV dimension fell below the recommended threshold of 0.50, indicating potential issues with convergent validity for this construct (Fornell & Larcker, 1981). These findings suggest that the SOV dimension may possess distinct characteristics compared to the other dimensions and that its contribution to the overarching construct is limited. Therefore, further evaluation of the items within this dimension is warranted to ensure that the indicators more accurately reflect the intended construct.

Despite the stronger inter-correlations among the other dimensions, a multidimensional approach was retained due to the SOV dimension's weaker correlations with the other factors and its relatively limited contribution, which supports the conceptual complexity of the broader online victimization construct.

To further assess the dimensionality of this construct, the use of a bifactor CFA model is recommended. The bifactor model would allow researchers to simultaneously evaluate the influence of a general factor and specific factors on the scale's items while also accounting for metrics such as

Explained Common Variance (ECV) and Omega Hierarchical (ωH) to determine the dominance of the general factor in explaining item variance (Reise et al., 2010; Rodriguez et al., 2015). This approach would provide a more nuanced understanding of the factor structure underlying the online victimization scale.

Additionally, the study did not include a clinical sample, which may limit the scale's applicability to milder online victimization typically experienced by the general population. Future research is advised to include individuals who have experienced more severe forms of online victimization, such as serious harassment, threats, or digital exploitation, in order to enhance the scale's validity in capturing the full spectrum of online victimization experiences (Meredith, 1993).

Finally, the convergent validity of this scale also requires further examination through comparisons with well-established instruments recognized as gold standards in the measurement of online victimization. Future studies are therefore encouraged to assess this scale against validated instruments to ensure its accuracy in capturing the intended construct.

Conclusion

This study confirms that the Online Victimization Scale (OVS) is a valid and reliable instrument for measuring online victimization across four dimensions: general online victimization, sexual online victimization, individual online racial discrimination, and vicarious online racial discrimination. Item selection based on error correlations resulted in a final scale comprising 16 items. Model comparisons indicated that the first-order and second-order OVS models exhibited comparable model fit, with no significant differences in fit indices. Moreover, measurement invariance testing demonstrated that the OVS achieved scalar invariance, indicating that the scale maintains equivalent factor loadings and item intercepts across different groups. These findings provide strong support for the use of the OVS in assessing online victimization across diverse populations.

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Conflict of Interest

Declaration by the authors that they do not have any conflicts of interest to declare.

Authors Contribution

MDM is responsible for data analysis, item development, methodology drafting, organizing results, writing the discussion, and conducting field data collection. AAA is tasked with determining the research topic, reviewing research reports, providing guidance, conducting data analysis, and drafting the methodology. MMM is assigned to draft the introduction, research methodology, and discussion, collect field data, and perform data analysis.

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Appendix

Instrument

No	*Pernyataan*	TP	J	KK	SR	SL
GOV8	*Saya enggan berpendapat karena takut diserang netizen*	1	2	3	4	5
GOV12	*Saya pernah menjadi korban pemalsuan identitas untuk menipu orang lain*	1	2	3	4	5
GOV13	*Saya telah diganggu secara online*	1	2	3	4	5
GOV14	*Orang-orang memposting hal-hal jahat atau kasar tentang saya di internet*	1	2	3	4	5
GOV19	*Saya pernah terpojokkan di grup WhatsApp, atau grup lainnya*	1	2	3	4	5
SOV4	*Saya pernah mendapatkan paksaan saat saya menolak mengirim foto atau video vulgar*	1	2	3	4	5
SOV5	*Saya ditanya mengenai riwayat sexual saya oleh orang yang kurang begitu dekat*	1	2	3	4	5
SOV7	*Saya pernah mendapat panggilan video chat vulgar (Ome TV, Omegle, MatchAndTalk dan Holla) dari orang asing*	1	2	3	4	5
SOV11	*Saya mendapatkan komentar tidak senonoh pada postingan saya*	1	2	3	4	5
IORD3	*Di sosial media saya dianggap kampungan saat menggunakan bahasa daerah*	1	2	3	4	5
IORD9	*Di sosial media saya diilecehkan oleh seseorang (misalnya troll) yang memulai argumen rasis tentang saya tanpa alasan*	1	2	3	4	5
IORD10	*Saya menerima hinaan rasis mengenai profil online saya (misalnya gambar profil, ID pengguna)*	1	2	3	4	5
IORD11	*Orang-orang meledek saya di sosial media karena logat yang saya miliki*	1	2	3	4	5
VORD4	*Melihat video online (misalnya YouTube) yang menggambarkan kelompok ras/etnis saya secara negatif*	1	2	3	4	5
VORD7	*Di sosial media saya melihat pengguna ras/minoritas lain diancam untuk disakiti atau dibunuh*	1	2	3	4	5
VORD8	*Di sosial media saya melihat pengguna ras/minoritas lain diperlakukan seperti warga negara kelas dua*	1	2	3	4	5

**Notes:*

TP = Tidak Pernah

J = Jarang

KK = Kadang-Kadang

SR = Sering

SL = Selalu

Syntax R

```
# Load Packages
library(lavaan)
library(semPlot)
```

```
library(readxl)

# Inspect Data
str(Data)

# Initial Model
model.initial <-'
  GOV =~ GOV1 + GOV2 + GOV3 + GOV4 + GOV5 + GOV6 + GOV7 + GOV8 + GOV9 +
GOV10 +
         GOV11 + GOV12 + GOV13 + GOV14 + GOV15 + GOV16 + GOV17 + GOV18 +
GOV19 + GOV20
  SOV =~ SOV1 + SOV2 + SOV3 + SOV4 + SOV5 + SOV6 + SOV7 + SOV8 + SOV9 +
SOV10 + SOV11 + SOV12
  IORD =~ IORD1 + IORD2 + IORD3 + IORD4 + IORD5 + IORD6 + IORD7 + IORD8 +
IORD9 + IORD10
  VORD =~ VORD1 + VORD2 + VORD3 + VORD4 + VORD5 + VORD6 + VORD7 + VORD8 +
VORD9 + VORD10 + VORD11

  GOV ~~ SOV
  GOV ~~ IORD
  GOV ~~ VORD
  SOV ~~ IORD
  SOV ~~ VORD
  IORD ~~ VORD
'

# First-order Model (16 Items)
model.first.order <- '
  GOV =~ GOV8 + GOV12 + GOV13 + GOV14 + GOV19
  SOV =~ SOV4 + SOV5 + SOV7 + SOV11
  IORD =~ IORD3 + IORD9 + IORD10 + IORD11
  VORD =~ VORD4 + VORD7 + VORD8

  GOV ~~ SOV
  GOV ~~ IORD
  GOV ~~ VORD
  SOV ~~ IORD
  SOV ~~ VORD
  IORD ~~ VORD
'

# Second-order Model (16 Items)
model.second.order <- '
  GOV =~ GOV8 + GOV12 + GOV13 + GOV14 + GOV19
  SOV =~ SOV4 + SOV5 + SOV7 + SOV11
  IORD =~ IORD3 + IORD9 + IORD10 + IORD11
  VORD =~ VORD4 + VORD7 + VORD8

  Online.Victimization =~ GOV + SOV + IORD + VORD
'

# Model Fit
out <- cfa(model.first.order, data = Data, std.lv = T)

summary(out, fit.measures = TRUE, standardized = T)

fit.indices <- fitMeasures(out, c("GFI", "AGFI"))
print(fit.indices)

# Modification Indices
mod.indices <- modindices(out)
mod.indices.resid <- subset(mod.indices, op == "~~" & lhs != rhs)
print(mod.indices.resid)
```

```
# Plot CFA
semPaths(out,
         what = "std",
         layout = "tree",
         title = T,
         style = "ram",
         posCol = 1.1,
         sizeMan = 7,
         sizeLat = 14,
         edge.label.cex = 1.2,
         label.cex = 1.2,
         cut = 0.01,
         nCharNodes = 0,
         curvePivot = T)

# Sample Moments
Nobs <- lavInspect(out, "nobs")
var.table <- lavNames(out, type = "ov")
Nvar <- length(var.table)
N.moments <- Nvar * (Nvar + 1) / 2
print(paste("Number of sample moments:", N.moments))

# Measurement Invariance (Multi-group CFA)
# Configural Invariance
fit.configural <- cfa(model.first.order, data = Data, std.lv = T, group =
"Gender")
summary(fit.configural, fit.measures = TRUE, standardized = T)

# Metric Invariance
fit.metric <- cfa(model.first.order, data = Data, std.lv = T, group =
"Gender", group.equal = "loadings")
summary(fit.metric, fit.measures = TRUE, standardized = T)

# Comparison of Configural-Metric Models
anova(fit.configural, fit.metric)
fitMeasures(fit.configural, c("cfi", "tli", "rmsea", "srmr", "chisq",
"df"))
fitMeasures(fit.metric, c("cfi", "tli", "rmsea", "srmr", "chisq", "df"))

# Scalar Invariance
fit.scalar <- cfa(model.first.order, data = Data, std.lv = T, group =
"Gender", group.equal = c("loadings", "intercepts"))
summary(fit.scalar, fit.measures = TRUE, standardized = T)

# Comparison of Metric-Scalar Models
anova(fit.metric, fit.scalar)
fitMeasures(fit.metric, c("cfi", "tli", "rmsea", "srmr", "chisq", "df"))
fitMeasures(fit.scalar, c("cfi", "tli", "rmsea", "srmr", "chisq", "df"))
```