Jurnal Psikologi
Volume 51, Number 3, 2024: 246 – 271
DOI: 10.22146/jpsi.94747

ISSN 0215-8884 (print)
ISSN 2460 867X (Online)

The Indonesian Version of the Online Learning Motivated Attention and Regulatory Strategies (OL-MARS v.2) Scale

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Submission 11 March 2024 **Accepted 18 October 2024** **Published 30 December 2024**

Abstract. The increasing use of ICT and the tendency for media multitasking among students have raised concerns about their negative impact on attention and the challenges they pose to regulation strategies. This study aimed to adapt and validate the Indonesian version of the Online Learning Motivated Attention and Regulatory Strategies (OL-MARS v.2) scale among undergraduate university students. The OL-MARS v.2 is a 24-item scale measuring two main constructs: Perceived Attention Problems (PAP) and Self Regulatory Strategies (SRS). PAP includes three subscales: Perceived Attention Discontinuity (PAD), Lingering Thoughts (LT), and Social Media Notifications (SMN), while SRS comprises Behavioral Strategies (BS) and Outcome Appraisal (OA). The scale was administered to 1,360 undergraduate students at a private university in Indonesia. Alpha coefficients for the total scores ranged from 0.463 to 0.800, indicating overall good to acceptable reliability, although the LT subscale showed the lowest alpha (0.463), which was acceptable but not ideal. Confirmatory factor analysis (CFA) was performed to evaluate the model fit. The OL-MARS v.2 shows potential as a valuable tool for assessing students' attention states and self-regulation strategies in online learning environments.

Keywords: attention states; media multitasking; OL-MARS v.2; regulation strategies; reliability and validity

Web access and various gadgets have enhanced students' learning experiences by providing personalized tools and services (Kompen et al., 2019). Applied technologies like computer-based learning, networked learning, and e-learning are examples of educational innovation (Serdyukov, 2017) that offer numerous benefits, including cost savings (Maatuk et al., 2022) and increased accessibility (Wu, 2017). However, the Internet, which has emerged as a crucial learning platform in higher education (Wu, 2015) with its multifaceted stream of information, can also lead to attentional switching and multitasking rather than sustained focus (Firth et al., 2019), potentially impair cognitive abilities (Voinea et al., 2020), and be linked to lower academic performance (le Roux & Parry, 2017).

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As with social media platforms in the 2000s, educational platform providers are expanding their "walled gardens" to include various user practices, resulting in classrooms on platforms instead of in traditional schools (Selwyn et al., 2020). Selwyn et al. (2020) likewise stated that "artificial intelligence will increasingly become the engine of education, and student data the fuel" (p.2). Digital technologies are becoming ever more prevalent among university students (Henderson et al., 2017), with high levels of digital media use becoming a feature of lectures (Castañeda & Selwyn, 2018; Parry et al., 2020). While smartphones are useful for learning, habitual use can negatively impact thinking, memory, attention, and emotion regulation, despite their flexibility and power when used responsibly (Wilmer et al., 2017).

Consequently, multitasking with media daily can lead to decreased attention control (Moisala et al., 2016) and challenges in students' attention allocation due to different task demands and limited attentional ability. Sato et al. (2023) explain that multitasking requires operators to balance tasks with limited attentional resources. Thus, maintaining student attention at the initial stage of remote learning is crucial. As Jamil et al. (2023) stated, the human brain is highly efficient at processing information but has limited capacity to handle multiple inputs and memories simultaneously. Wu (2017) reminded us that "failure to regulate attention can lead to concurrent engagement in multiple media applications that are irrelevant to learning (e.g., texting, online chatting, non-homework-related Internet use)" (p.57). Limited cognitive resources can also lead to detrimental effects on learning when students engage in off-task activities through digital media (Wu, 2017).

Therefore, understanding students' attention states and how they regulate their attention while studying is critical in the age of digital distraction (Wu & Cheng, 2019). To achieve a satisfying outcome, students should allocate their attention, directing it toward tasks related to the study topic and applying suitable regulatory strategies when learning online and multitasking with digital media (M. W. Johnson & Sherlock, 2014; Wu, 2017). Wu (2015) previously developed the Online Learning Motivated Attention and Regulatory Strategies (OL-MARS) scale to assess students' attention states and use of regulation strategies during online learning. He then extended the scale to reveal that perceived attention problems and self-regulation strategies mediate the relationship between media multitasking self-efficacy and learning performance (Wu, 2017). Wu and Cheng (2019) also published their OL-MARS-based research findings, which examined gender differences in college students' media-related attention problems and attention self-regulation strategies, as well as the moderating effects of these issues on social media usage, online search strategies, media multitasking self-efficacy, self-esteem, and academic achievement. The results demonstrate that the OL-MARS is a viable and relevant measurement tool.

Additionally, Randjelovic and Kostic (2022) used the OL-MARS and the Achievement Emotions Questionnaire Short Version (AEQ-S) to study how Serbian students employ digital diversions during boredom. The findings support prior research indicating that unpleasant emotions during instruction create attention problems, i.e., when students become bored, they turn to various digital distractions to divert their attention. Given the growing popularity of online education, these findings show that the OL-MARS could help assess the challenges of students enrolled in courses through online platforms.

Assessments using the OL-MARS are valuable and could also be applied to the Indonesian context for the following reasons: Cambridge International's research reveals that Indonesian students are among the highest users of technology in education, often outperforming students from more developed countries, and their technology use in the classroom is higher than in other countries as well. Indonesian students use computer rooms at the highest rate globally (40%). They also rank second highest in the world in desktop computer use (54%), after the United States. In addition, more than two-thirds of Indonesian students (67%) use smartphones in class, and even more use them to do homework (81%). Likewise, in several Indonesian universities and vocational colleges, the Internet has become an important part of the teaching and learning process (BBC News Indonesia, 2018).

Furthermore, the 2024 Asosiasi Penyelenggara Jasa Internet Indonesia (Indonesian Internet Service Providers Association, or APJII) study found that the number of Internet users in Indonesia is increasing and is dominated by millennials. From 2023 to 2024, Indonesia's Internet user penetration increased by 1.31%, from 78.19% to 79.5% (Arif, 2024). Undeniably, social media usage, often categorized as Internet usage (Cataldo et al., 2021), has significantly impacted daily functioning (Cudo et al., 2019), leading students to multitask and affecting focus, attention, and regulatory strategies, especially when studying online. Thus, critical Indonesian educational researchers must examine the impact of ICT use and media multitasking on students' attentional capabilities, particularly the propensity to multitask while studying (Carrier et al., 2015). A dependable instrument is needed to facilitate their research in these areas.

To the author's knowledge, there have been at least two valuable studies regarding media multitasking in Indonesia using the Media Multitasking Index (MMI) developed by Ophir et al. (2009). Fatmawati (2017) highlighted the importance of understanding multitasking for librarians. Wiradhany and Nieuwenstein (2017) analyzed the relationship between distractor filtering and media multitasking. However, they stated that the evidence for the relationship between multitasking and distractibility was equivocal. Conversely, a study employing the OL-MARS v.2 found a correlation between secondary school students' decreasing attention and internet and social media use (Gani, 2022). This indicates that the OL-MARS v.2 can be a useful measuring instrument for investigating such interactions, even in specific aspects, and providing valuable information. Yet, following a thorough study of the available scholarly literature, we uncovered no prior adaptation or validation of the OL-MARS v.2 in Indonesia. This study therefore aims to adapt the scales to assess students' attention states and regulatory strategies during media multitasking. Additionally, it offers empirical evidence for their internal consistency, reliability, and validity in Indonesian populations, notably among undergraduate university students. As a result, the OL-MARS v.2 can help to close the literature gap.

Methods

This study employed a quantitative approach using a survey research method. In summary, the study was carried out in three stages: 1) the adaptation of the English version of the OL-MARS v.2 to the Indonesian version, 2) the distribution of the adapted version to the study population, and 3) the data analysis process.

Adaptation and Translation

At the initial stage, the authors requested the original OL-MARS v.2 and permission from Jiun-Yu Wu, Ph.D., the scale developer and owner, in direct correspondence via email. After obtaining the original scales and permission to adapt the OL-MARS v.2, the next stage was doing the back-translation (Behr, 2017). This study adapted and back-translated the OL-MARS v.2 from the English version into the Indonesian version using the Brislin model for instrument translation (Brislin, 1970; Jones et al., 2001). The Brislin back-translation model is a well-known method for cross-cultural research (Cha et al., 2007). In it, a bilingual translator translates the instrument from the source to the target language, and a second bilingual translator independently reverses the translation from the target to the source language without knowing the original version. The original and back-translated versions of the instrument are then compared to ensure idea similarity.

Next, we examined and discussed the translated Indonesian version. There was no error discovered in the back-translation (Table 2), so the Indonesian version was sent to Jiun-Yu Wu, Ph.D., the original author of the OL-MARS v.2 (Gani, 2022). It was then given to two fellow lecturers to check for content validity and readability. Following this process readability testing was also conducted with ten university students to see whether the research population could comprehend the instructions and material without difficulty.

Participants

We used convenience sampling, which selects participants from the target population based on accessibility (Golzar & Noor, 2022; Stratton, 2021), to survey college students at a private institution in Surabaya, Indonesia. We acknowledge that employing a larger sample through a convenience sampling strategy allows for slightly better generalization, but the lack of random participant selection means that selection bias restricts the generalizability of findings on a large scale (Emerson, 2021). Therefore, due to its considerable bias, the sample in this study is unique and may not accurately represent the greater population. The results of this study may only reflect the ideas of the selected group, and this should be considered carefully.

On October 24, 2018, printed questionnaires were handed out to first-year students taking an in-class ethics course at the target institution. The questionnaire examined the relationship between Internet and social media use, media multitasking self-efficacy with attention methods, and self-regulation in online learning. The initial page of the survey stated that responses were anonymous, participants should not provide incorrect answers, and the decision to participate or not would not affect their rights or final grades. The responses were assessed for internal consistency, reliability, and validity. Initially, 1,416 of the undergraduate students participated: 796 boys and 620 girls. However, 56 students' responses were removed after testing for outliers because they were incomplete or did not reflect most observations. Thus, 1,360 students (768 males and 592 females) were included in the final study. The sample's average age is 17.96 years (MIN = 16, MAX = 23, mean = 17.96 years).

Instruments

The questionnaire consisted of two sections. The first part, questions about electronic devices, social media, and online activities, required students to report their demographic information; devices they used; and time spent on the Internet, Facebook, and other social media accounts (Instagram, Twitter, LinkedIn, and Path), including average time spent on the Internet per day; average time spent on Facebook and other social media accounts per hour; and average number of visits to Facebook and other social media accounts. Responses were rated on a Likert scale to prevent extreme values.

The second part of the questionnaire is the Indonesian OL-MARS v.2. It required students to report their perceived attention state and regulatory strategies in online learning. The Indonesian version of the OL-MARS v.2 comprises 24 items in two constructs of engagement in multitasking, namely, Perceived Attention Problems (PAP) and Self-Regulatory Strategies (SRS). PAP includes three subscales: lingering thoughts (4 items), social media notifications (3 items), and perceived attention discontinuity (8 items), while SRS includes two subscales: outcome appraisal (3 items) and behavioral strategies (6 items). Responses were scored using a five-point scale with one indicating extreme disagreement and five indicating extreme agreement.

Data Analysis Procedures

The data were analyzed using SPSS version 21 and the AMOS add-on package, and after screening for outliers on numerous variables using Boxplot, the data obtained included 1,360 responses. Cronbach's alpha (α) was calculated for each subscale to assess the questionnaire's internal consistency and reliability. A questionnaire can be used for multiple samples, locations, and periods if the alpha coefficient value is more than or equal to 0.60 (Malhotra & Dash, 2016). Values of $\geq$ 0.70 were considered satisfactory (Bland & Altman, 1997; Taber, 2018), and values between 0.50 and 0.70 were considered to show moderate reliability (Hinton et al., 2004). Item-total correlation tests and Confirmatory Factor Analysis (CFA) were then employed to assess the psychometric features.

CFA tests whether a specified set of factors adequately predicts the variations in observed variables (Shek & Yu, 2014). CFA is a theoretical way to determine how well a given factor model fits observable data. This fit assessment technique is based on Bentler and Bonett (1980), as cited in Laar et al. (2021) and uses a variety of models, from the worst-fitting null model to the best-fitting or saturated model. The comparative fit indices indicate where the model of interest sits on this continuum. It also ensures that evaluation tools adhere to theory and contain adequately classified elements (Natalya & Purwanto, 2018) as cited in Ishak and Elgeka (2023). Hence, this study follows up with basic structural equation modeling (SEM) using SPSS AMOS (Tables 5 and 6).

Results

The Adaptation Process from the English Version of OL-MARS v.2 to the Indonesian Version

After receiving the original English version and permission from the developer and owner of the OL-MARS v.2 scales (Wu, 2017), the authors altered, translated, and back-translated the items.

Cross-cultural translation aims for equivalency between two different languages (Cha et al., 2007; Choi et al., 2012; Jones et al., 2001; Lee et al., 2009). Table 2 shows the translated and back-translated versions provided by each translator. Due to space constraints, we have divided the translations of the OL-MARS v.2 instructions (Table 1) and items (Table 2).

Table 1

OL-MARS v.2 Instructions

Original Version in English Instructions: The following statements reflect various ways in which you may describe your computer and internet experience. Rate the degree to which you feel each statement describes your experience using the following scale (1 = Not at all like me; 5 = Very much like me). There is no right or wrong answer.	Not at all like me 1	Not much like me 2	Neutral 3	Some what like me 4	Very much like me 5
Translation to the Target Language *Petunjuk*: *Pernyataan berikut mencerminkan berbagai cara untuk menggambarkan pengalaman komputer dan Internet Anda. Beri nilai pada tingkat di mana Anda merasa setiap pernyataan menggambarkan pengalaman Anda menggunakan skala berikut*: 1 = *Sama sekali tidak seperti saya*; 5 = *Sangat seperti saya. Tidak ada jawaban benar atau salah*.	*Sama sekali tidak seperti saya* 1	*Tidak seperti saya* 2	Netral 3	*Agak seperti saya* 4	*Sangat seperti saya* 5
Back Translation to the Source Language Directions: The following statements reflect various ways to describe your computer and Internet experiences. Rate the levels at which you feel each statement describes your experience using the following scale: 1 = Not at all like me; 5 = Very like me. There is no right or wrong answer.	Not at all like me 1	Not like me 2	Neutral 3	Some what like me 4	Very like me 5

Table 2

The Translation and Back-Translation of OL-MARS v.2

No	Original Version in English	Translation to Indonesian, the Target Language	Agreed Translation after Group Discussion	Back Translation to English, the Source Language
PAD 1	I turn on the computer in order to do my homework, but I still visit Facebook first.	*Saya menyalakan komputer untuk melakukan PR saya, tetapi saya tetap mengunjungi Facebook terlebih dahulu.*	*Saya menyalakan komputer untuk mengerjakan PR saya, tetapi saya tetap mengunjungi Facebook lebih dahulu.*	I turn on the computer to do my homework, but I still visit Facebook first.
PAD 2	I visit websites or open software that are irrelevant to my learning when using the Internet for my project or studies.	*Saya mengunjungi situs Web atau membuka perangkat lunak yang tidak relevan dengan pembelajaran saya, ketika menggunakan Internet untuk proyek atau penelitian saya.*	*Saya mengunjungi situs Web atau membuka perangkat lunak yang tidak relevan dengan pembelajaran saya, ketika menggunakan Internet untuk proyek atau penelitian saya.*	I visit websites or open software that is not relevant to my learning, when using the Internet for my project or to do my research.
PAD 3	I often click the links of interesting ads, pictures, or articles unconsciously when using computers to search information for my project.	*Saat menggunakan komputer untuk mencari informasi untuk proyek (tugas kuliah), tanpa disadari saya sering mengeklik tautan iklan, gambar, atau artikel-artikel menarik lainnya.*	*Saat menggunakan komputer mencari informasi untuk proyek (tugas kuliah), tanpa disadari saya sering mengeklik tautan iklan, gambar, atau artikel-artikel menarik lainnya.*	When using the computer to find information for a project (college assignment), I unwittingly click the links for ads, pictures, or other interesting articles.
PAD 4	I often turn on the computer for work (e.g., writing paper, learning, or searching information), but find myself always doing other things (e.g., watching YouTube, checking Facebook, reading online news, or playing games).	*Saya sering menyalakan komputer untuk bekerja (misalnya menulis makalah, belajar atau mencari informasi), namun mendapati diri saya selalu melakukan hal-hal lain (misalnya menonton YouTube, memeriksa Facebook, membaca berita online, atau bermain game).*	*Saya sering menyalakan komputer untuk bekerja (misalnya menulis makalah, belajar atau mencari informasi), namun mendapati diri saya selalu melakukan hal-hal lain (misalnya, menonton YouTube, memeriksa Facebook, membaca berita online, atau bermain game).*	I often turn on the computer to work (e.g., writing papers, studying, or looking for information), but find that I always do other things (like watching YouTube, checking Facebook, reading news online or playing games).

Table 2 (Continued)
The Translation and Back-Translation of OL-MARS v.2

No	Original Version in English	Translation to Indonesian, the Target Language	Agreed Translation after Group Discussion	Back Translation to English, the Source Language
PAD 5	I turn on computer to do my work, but I still visit other websites or use other computer programs (e.g., games, YouTube, news) instead.	*Saya menyalakan komputer untuk melakukan pekerjaan saya, namun saya tetap mengunjungi situs Web lain atau menggunakan program komputer lain (misalnya games, YouTube, berita-berita).*	*Saya menyalakan komputer untuk melakukan pekerjaan saya, namun saya tetap mengunjungi situs Web lain atau menggunakan program computer lain (misalnya games, YouTube, berita-berita).*	I turn on the computer to do my work, but I keep visiting other websites or using other computer programs (e.g., games, YouTube, news).
PAD 6	I know I have attention problems when using computers to learn or to do my homework.	*Saya tahu saya memiliki masalah perhatian saat menggunakan komputer untuk belajar atau mengerjakan PR saya.*	*Saya tahu saya memiliki masalah perhatian saat menggunakan komputer untuk belajar atau mengerjakan PR saya.*	I know I have attention problems when using a computer to learn or do my homework.
PAD 7	I often visit Facebook or other social network sites unconsciously when using computers to do my homework or to learn online.	*Saat saya menggunakan komputer untuk mengerjakan PR atau belajar secara online, tanpa disadari saya sering mengunjungi Facebook atau situs jejaring sosial lainnya.*	*Saat saya menggunakan komputer untuk mengerjakan PR atau belajar online, tanpa disadari saya sering mengunjungi Facebook atau situs jejaring sosial lainnya.*	When I use my computer to do my homework or study online, I often do not realize that I am visiting Facebook or various other social media sites.
PAD 8	If I encounter difficulties when using the Internet for studying, I will open other programs, websites, or check my smartphone unconsciously.	*Jika saya mengalami kesulitan saat menggunakan Internet untuk belajar, saya akan membuka program lain, situs Web, atau memeriksa ponsel cerdas saya secara tidak sadar.*	*Jika saya mengalami kesulitan saat menggunakan Internet untuk belajar, saya akan membuka program lain, situs Web, atau memeriksa ponsel cerdas saya secara tidak sadar.*	If Im having trouble when using the Internet to learn, Ill open another program, website, or check my smartphone unconsciously.
BS 1	When learning, I log out my Facebook account or close instant messaging software, so that I can focus on my work.	*Saat belajar, saya logout akun Facebook atau tutup perangkat lunak pesan instan, sehingga saya bisa fokus pada tugas saya.*	*Saat belajar, saya keluar dari akun Facebook atau menutup perangkat lunak pesan instan, sehingga saya bisa fokus pada pekerjaan saya.*	While studying, I logout my Facebook account or close the instant messaging software, so I can focus on my task.

Table 2 (Continued)
The Translation and Back-Translation of OL-MARS v.2

No	Original Version in English	Translation to Indonesian, the Target Language	Agreed Translation after Group Discussion	Back Translation to English, the Source Language
BS 2	In order to focus on learning on the Internet, I close unrelated websites or turn off the sounds.	*Agar fokus belajar di Internet, saya menutup situs Web yang tidak terkait atau mematikan suaranya.*	*Agar focus belajar di Internet, saya menutup situs Web yang tidak terkait atau mematikan suaranya.*	In order to focus on learning on the Internet, I closed unrelated websites or turn off notifications.
BS 3	I use strategies to help myself focus on my work (e.g., unplugging, closing unrelated windows, or limiting the speed of upload/ download) when using computers.	*Saya menggunakan strategi untuk membantu diri fokus pada pekerjaan saya (misalnya mencabut, menutup "jendela" yang tidak terkait, atau membatasi kecepatan mengunggah atau mengunduh saat menggunakan komputer).*	*Saya menggunakan strategi untuk membantu diri saya fokus pada pekerjaan saya (misalnya, mencabut steker, menutup "jendela" yang tidak terkait, atau membatasi kecepatan mengunggah atau mengunduh saat menggunakan komputer).*	I use strategies to help myself focus on my work (e.g., pulling out or closing windows that do not related, or limit the speed of upload/ download when using the computer).
BS 4	I tell myself to complete the scheduled assignment or work first before visiting websites or playing games that I like.	*Saya memberitahu diri saya untuk menyelesaikan tugas yang telah dijadwalkan atau bekerja terlebih dahulu sebelum mengunjungi situs Web atau bermain game yang saya sukai.*	*Saya berkata pada diri sendiri untuk menyelesaikan tugas yang telah dijadwalkan atau bekerja terlebih dahulu sebelum mengunjungi situs Web, atau bermain game yang saya sukai.*	I tell myself to complete a scheduled task or planned work first before visiting websites or playing games I like.
BS 5	If I postponed what I should be doing because of using the Internet, I try to avoid doing this next time.	*Jika saya menunda apa yang seharusnya saya lakukan karena menggunakan Internet, saya mencoba menghindari hal ini di lain waktu.*	*Jika saya menunda apa yang seharusnya saya lakukan karena menggunakan Internet, saya mencoba menghindari hal ini di lain waktu.*	If I postpone what I should do because I use the Internet, I try to avoid doing this again at a later time.
BS 6	When I notice that I am browsing unrelated websites or playing games, I ask myself to turn back to what I should do (e.g., writing paper, learning, or searching for information).	*Ketika saya menyadari bahwa saya menjelajahi situs web yang tidak terkait atau bermain games, saya meminta diri saya untuk kembali kepada apa yang harus saya lakukan (misalnya menulis makalah, belajar, atau mencari informasi).*	*Ketika saya menyadari bahwa saya menjelajahi situs Web yang tidak terkait atau bermain games, saya meminta diri saya untuk kembali kepada apa yang harus saya lakukan (misalnya menulis makalah, belajar, atau mencari informasi).*	When I realized that I was exploring unrelated websites or playing games, I ask myself to go back to what I should do (e.g., writing a paper, studying, or looking for information).

Table 2 (Continued)

The Translation and Back-Translation of OL-MARS v.2

No	Original Version in English	Translation to Indonesian, the Target Language	Agreed Translation after Group Discussion	Back Translation to English, the Source Language
LT 1	When studying, I often feel that something is interesting happening on the Internet.	*Ketika belajar, saya sering merasa ada sesuatu yang menarik terjadi di Internet.*	*Ketika belajar, saya sering merasa ada sesuatu yang menarik terjadi di Internet.*	While studying, I often feel there is something interesting happening on the Internet.
LT 2	When using the computer for studying, I think of what I want to eat later or what I have just eaten.	*Saat menggunakan komputer untuk belajar, saya memikirkan apa yang ingin saya makan nanti atau apa yang baru saja saya makan.*	*Saat menggunakan komputer untuk belajar, saya memikirkan apa yang ingin saya makan nanti atau apa yang baru saja saya makan.*	When using the computer to learn, I think about what I want to eat or what Ive just eaten.
LT 3	When using the computer for studying, I notice what people nearby are doing or talking about.	*Saat menggunakan komputer untuk belajar, saya memperhatikan apa yang dilakukan atau dibicarakan orang-orang terdekat.*	*Saat menggunakan komputer untuk belajar, saya memperhatikan apa yang sedang dilakukan atau dibicarakan oleh orang-orang di sekitar.*	When using the computer to learn, I pay attention to what people around me do or talk about.
LT 4	When using the computer for studying, I cant help but feel like playing mobile games unconsciously.	*Saat menggunakan komputer untuk belajar, saya tidak berdaya dan tanpa sadar merasa seperti sedang bermain games.*	*Saat menggunakan komputer untuk belajar, saya tidak berdaya dan tanpa sadar merasa seperti sedang bermain games.*	While using the computer to learn, I feel helpless and unknowingly feel like I am playing games.
OA 1	If I postponed what I should be doing because of using the Internet, I feel guilty.	*Jika saya menunda apa yang seharusnya saya lakukan karena menggunakan Internet, saya merasa bersalah.*	*Jika saya menunda apa yang seharusnya saya lakukan karena menggunakan Internet, saya merasa bersalah.*	If I postpone what I should do because I use the Internet, I feel guilty.
OA 2	When I notice that I am browsing unrelated sites or playing computer games, I feel guilty.	*Saat saya menyadari bahwa saya melihat situs yang tidak terkait dengan belajar atau bermain game komputer, saya merasa bersalah.*	*Saat saya menyadari bahwa saya melihat situs yang tidak terkait dengan belajar atau bermain game komputer, saya merasa bersalah.*	When I realized that I visit a site that unrelated to learning or find myself playing computer games, I feel guilty.

Table 2 (Continued)

The Translation and Back-Translation of OL-MARS v.2

No	Original Version in English	Translation to Indonesian, the Target Language	Agreed Translation after Group Discussion	Back Translation to English, the Source Language
OA 3	If I focus on what I should be doing when using the computer (e.g., write paper, learn or search information), I feel happy and feel a sense of achievement.	*Jika saya fokus pada apa yang seharusnya saya lakukan ketika menggunakan komputer (misalnya menulis makalah, belajar atau mencari informasi), saya merasa bahagia atau merasakan suatu pencapaian.*	*Jika saya fokus pada apa yang seharusnya saya lakukan ketika menggunakan komputer (misalnya menulis makalah, belajar atau mencari informasi), saya merasa senang dan merasakan suatu pencapaian.*	If I focus on what I should do when using a computer (e.g., writing a paper, studying or looking for information), I feel happy and feel that I have attained an achievement.
SMN 1	When I see or hear notifications from social media (e.g., Twitter, Instagram, Facebook.. etc.), I cannot wait to check them.	*Saat saya melihat atau mendengar pemberitahuan dari sosial media* (*mis.* Twitter, Instagram, Facebook..dll) *saya tidak sabar untuk memeriksanya.*	*Saat saya melihat atau mendengar notifikasi dari sosial media* (*mis.* Twitter, Instagram, Facebook.. *dll*) *saya tidak sabar untuk memeriksanya.*	When I see or hear notifications from social media (e.g., Twitter, Instagram, Facebook..etc.) I cannot wait to check those sites.
SMN 2	*When studying, I immediately notice the alerts from instant messaging software* (such as LINE, texting, or WhatsApp).	*Ketika belajar, saya segera melihat peringatan* (alerts) *dari perangkat lunak pesan instan* (*seperti* LINE, texting, *atau* WhatsApp).	*Ketika belajar, saya segera melihat peringatan* (notifikasi) *dari perangkat lunak pesan instan* (*seperti* LINE, texting, *atau* WhatsApp).	When learning, I immediately see alerts from instant messaging software (like LINE, texting, or WhatsApp).
SMN 3	When I hear notifications from cellphones or tablets, I check them immediately.	*Saat saya mendengar notifikasi dari ponsel atau tablet, saya segera memeriksanya.*	*Saat saya mendengar notifikasi dari ponsel atau tablet, saya segera memeriksanya.*	When I hear notifications from my phone or tablet, I check it out right away.

Table 2 indicates that these elements are relatively easy to translate. Only a few minor discrepancies exist between the source language version and the target language translation. The differences highlighted in italics were not erroneous and they did not alter the meaning of the phrases. For example, in item 1, the original phrases “other social network sites” and “to learn” were back-translated to "various other social media sites" and “study.” In item 2, “unconsciously” in the original language was back-translated to “unwittingly”; in item 6, “that are irrelevant” in the original version was back-translated to “that is not relevant”; in item 7, “the scheduled assignment or work first” was translated to “a scheduled task or planned work first”; in item 8, “unplugging” was back-translated to “pulling out”; and in item 12, “I still visit other websites” was back-translated to “I keep visiting other websites."

Afterward, the translators discussed and suggested changes to some parts of the Indonesian translation before it was used. These did not change the items' meaning or aim, but was purely for language flexibility. Using their ideas, the authors made adjustments to ensure that the OL-MARS v.2 Indonesian version is equivalent to the original. There were no significant changes to the items' stated or suggested meaning.

Readability Tests

Two lecturers and ten university students from another city performed readability tests. The students who participated matched the scale's target demographic. All respondents regarded the scale's items as easy to understand.

Internal Consistency and Reliability

Table 3 displays the internal consistency of the OL-MARS v.2. Internal consistency refers to the degree of interrelatedness between items, which is critical for providing accurate measurements (Natalya & Purwanto, 2018). Cronbach's alpha measures a scale's internal consistency, or item interrelatedness (Cortina, 1993; E. Johnson, 2021). The alpha values proved that the surveys were reliable, and overall, the alpha value for internal consistency was satisfactory. The total and subscale scores of the OL-MARS v.2 in the Indonesian sample show strong internal consistency as a type of reliability (Cheung et al., 2024; El-Den et al., 2020) with alpha values of 0.800 for SMN, 0.463 for LT, 0.781 for PAD, 0.720 for BS, and 0.653 for OA. The values for each subscale are as follows: SMN (0.740, 0.753, 0.686), LT (0.381, 0.398, 0.455, 0.326), PAD (0.746, 0.762, 0.739, 0.777, 0.752, 0.765, 0.747, 0.768), BS (0.719, 0.676, 0.670, 0.656, 0.686, 0.679), OA (0.553, 0.676, 0.404). The LTs alphas total value (.463) and items were the lowest and were not satisfactory, but acceptable (Hinton et al., 2004; Taber, 2018).

Table 3

Item Descriptive Statistics and Internal Consistency for the Indonesian OL-MARS V.2

Scale/Item	*M*	*SD*	Cronbach's α
Sample (*n* = 1360)			
OL-MARS v.2			
Perceived Attention Problems (PAP)			
Social Media Notifications (SMN) Total	10.829	2.632	.800
SMN 1	3.58	1.070	.740
SMN 2	3.68	.999	.753
SMN 3	3.55	1.033	.686
Lingering Thoughts (LT) Total	12.392	2.604	.463
LT 1	3.27	1.065	.381
LT 2	2.47	1.045	.398
LT 3	3.42	.995	.455
LT 4	3.23	1.056	.326

Table 3 (Continued)

Item Descriptive Statistics and Internal Consistency for the Indonesian OL-MARS v.2

Scale/Item Sample (n = 1360) OL-MARS v.2	M	SD	Cronbach's α
Perceived Attention Discontinuity (PAD) Total	26.798	5.448	.781
PAD 1	3.36	1.164	.746
PAD 2	2.93	1.170	.762
PAD 3	3.69	1.099	.739
PAD 4	3.19	1.091	.777
PAD 5	3.05	1.024	.752
PAD 6	3.02	1.162	.765
PAD 7	3.73	.979	.747
PAD 8	3.81	.911	.768
Self-Regulatory Strategies (SRS)			
Behavioral Strategies (BS) Total	19.432	3.987	.720
BS1	3.64	.984	.719
BS2	2.80	1.146	.676
BS3	2.72	1.124	.670
BS4	3.06	1.069	.656
BS5	3.63	.898	.686
BS6	3.52	.852	.679
Outcome Appraisal (OA) total	10.203	2.414	.653
OA1	3.04	1.125	.553
OA2	3.76	.950	.676
OA3	3.39	1.047	.404

Abbreviations used: Mean (M), Standard Deviations (SD)

Item Internal Consistency Reliability

Table 4 presents the internal consistency reliability analysis for the construct, two sub-constructs, and five subscales of the Indonesian OL-MARS v.2. All individual items showed significant adjusted item-total correlations in the subscales.

Table 4

Summary of Item Internal Consistency Reliability Analysis for Construct, Two Sub-construct, and Five Sub-scales for the Indonesian OL-MARS V.2

Scale/Item OL-MARS V.2	R= 0,052	Corrected Item-Total Correlation	Cronbach's Alpha If Item Deleted	N of Items
Sample (n = 1360)				

Table 4 (Continued)

Summary of Item Internal Consistency Reliability Analysis for Construct, Two Sub-construct, and Five Sub-scales for the Indonesian OL-MARS V.2

Scale/Item OL-MARS v.2	*R*= 0,052	Corrected Item-Total Correlation	Cronbach's Alpha If Item Deleted	*N* of Items
Perceived Attention Problems (PAP)				
Social Media Notifications (SMN)				3
SMN 1	0,052	,633	,740	
SMN 2	0,052	,620	,753	
SMN 3	0,052	,683	,686	
Lingering Thoughts (LT)				4
LT 1	0,052	,275	,381	
LT 2	0,052	,258	,398	
LT 3	0,052	,195	,455	
LT 4	0,052	,329	,326	
Perceived Attention Discontinuity (PAD)				8
PAD 1	0,052	,546	,746	
PAD 2	0,052	,462	,762	
PAD 3	0,052	,588	,739	
PAD 4	0,052	,365	,777	
PAD 5	0,052	,516	,752	
PAD 6	0,052	,444	,765	
PAD 7	0,052	,554	,747	
PAD 8	0,052	,414	,768	
Self-Regulatory Strategies (SRS)				
Behavioral Strategies (BS)				6
BS1	0,052	,321	,719	
BS2	0,052	,474	,676	
BS3	0,052	,492	,670	
BS4	0,052	,535	,656	
BS5	0,052	,443	,686	
BS6	0,052	,473	,679	
Outcome Appraisal (OA)				3
OA1	0,052	,469	,553	
OA2	0,052	,366	,676	
OA3	0,052	,571	,404	

Factor Analysis

The validity of the OL-MARS v.2 was tested using confirmatory factor analysis (CFA). CFA is a theory-driven approach that evaluates the fit of a preset model to observable data (Finch, 2020; Shek & Yu, 2014). It is widely used in psychology research to develop measurement models for psychological constructs. To assess the adequacy of the proposed models, we used a model-fit test and model-fit indices such as the Root Mean Square Error of Approximation (RMSEA), Goodness-of-Fit Index (GFI), the Normed Fit Index (NFI), and the non-NFI that is also known as the Tucker-Lewis index (TLI) (Goretzko et al., 2024).

Table 5

Results of The Model Fit Indices

Goodness of Fit	Cut of Value	Analysis Results	Model Evaluation
Probability	> 0.05	0.000	Marginal
GFI	> 0.90	0.837	poor fit
AGFI	> 0.80	0.815	acceptable fit
TLI	> 0.95	0.709	poor fit
NFI	> 0.95	0.700	poor fit
RMSEA	< 0.08	0.068	good fit

Table 6

Results of Factor Loading Coefficient

Variable	Standardized Regression Weights					*S.E*	*C.R*	*p*
	SMN	LT	PAD	BS	OA			
Item 1	0.735							
Item 2	0.758					0.04	23.975	***
Item 3	0.777					0.042	24.29	***
Item 4		0.661						
Item 5		0.415				0.056	11.058	***
Item 6		(0.199)				0.048	5.847	***
Item 7		0.341				0.054	9.454	***
Item 8			0.618					
Item 9			0.520			0.053	15.831	***
Item 10			0.664			0.053	19.098	***
Item 11			0.404			0.048	12.765	***
Item 12			0.567			0.048	16.963	***
Item 13			0.536			0.053	16.234	***
Item 14			0.646			0.047	18.731	***
Item 15			0.524			0.042	15.932	***
Item 16				0.387		0.048	11.838	***

Table 6 (Continued)

Results of Factor Loading Coefficient

Variable	Standardized Regression Weights		*S.E*	*C.R*	*p*
Item 17	0.548		0.059	15.829	***
Item 18	0.587		0.059	16.653	***
Item 19	0.627				
Item 20	0.574		0.047	16.388	***
Item 21	0.590		0.045	16.714	***
Item 22		0.610	0.046	17.89	***
Item 23		0.507	0.037	15.504	***
Item 24		0.792			

The *** sign is significant (< 0.001)

The ( ) is the item with the lowest factor loading

Table 5 presents the range of acceptable fit indices for confirmatory factor analysis. The RMSEA and AGFI are within acceptable ranges. However, the GFI, TLI, and NFI are below the expected values. In addition to utilizing the goodness-of-fit indices (GOFs) to decide the model, it is also essential to understand the significance of the factor loadings of each observed variable or question item to the construct/latent variable being assessed. The output result in Table 6 shows that each variable indicator meets the validity standards and reflects the variables (Suyatno et al., 2022). The convergent validity is shown when the Critical Ratio (*CR*) of each indicator is more than twice its standard error (*CR* > 2.0 SE). This means the indicator correctly measures what it should in the model (Waluyo, 2016). The results also meet the criteria: namely, a Critical Ratio (*CR*) value > 1.96 with a probability (p) < 0.05 (Andrade, 2019).

Discussion

The present study, a survey of 1,360 students aged 16 to 23, aimed to prove internal consistency as a type of reliability (Cheung et al., 2024; El-Den et al., 2020) and validity of the Indonesian OL-MARS v.2 (Tables 3, 4 and 6), with an end goal of measuring students' attention states and use of strategies for regulating their attention while studying and multitasking online using digital devices. The study showed that the two main constructs and five subscales have adequate and acceptable reliability. The item analysis indicated that the items contributed significantly to the instrument, although there are cases where the inter-item correlations within the sub-constructs and sub-scales were low.

When we compare the range of Cronbach's alpha between the original studies of the OL-MARS v.2 done by Wu (2017) (0.887 for PAD, 0.724 for LT, 0.774 for SMN, 0.774 for BS, and 0.694 for OA in a sample aged 18 to 48 years) and this study of the Indonesian version, it shows adequate internal consistency, except for one subscale (LT) of the Indonesian version, where Cronbach's alpha has a lower than desired value (Table 3). Nonetheless, the unsatisfactory results can be accepted with some reasons and explanations. According to Tavakol and Dennick (2011), alpha is based on the tau-equivalent model, which assumes that each test item measures the same latent trait on the same scale. If multiple factors or traits underlie items, alpha underestimates test reliability. Small test items also violate tau-equivalence. When test items meet the model's assumptions, alpha approaches a better estimate of reliability. Cronbach's alpha is a lower bound estimate due to heterogeneous test items. If the standardized item alpha is higher than Cronbach's alpha, further examination of the tau-equivalent measurement is necessary. More specifically, the length of a scale affects the value of alpha. Longer scale lengths, such as those with multiple scale elements, result in greater alpha values. A small number of scale items would contradict tau-equivalence, resulting in a reduced reliability coefficient. The value of alpha decreases for a short amount of time. As a result, short scales (scales with fewer than five elements) frequently have low Cronbach values (e.g., 0.50).

Therefore, the alpha value in a test is influenced by factors like the number of test items, interrelatedness, and dimensionality (Cortina, 1993). There are different reports about the acceptable values of alpha, ranging from 0.70 to 0.95. Low alpha may be due to low questions, poor interrelatedness, or heterogeneous constructs. Low correlations can be identified by computing each test item's correlation with the total score test, with items approaching zero being deleted (Tavakol & Dennick, 2011). Hinton et al. (2004) explained in their book that a Cronbach's alpha of 0.5 is acceptable, and they indicate that alpha values from 0.5 to 0.7 show moderate reliability. Sijtsma (2009) argued that reliability estimates based on a single test administration, such as alpha, may not provide sufficient information on the accuracy of individual test performance. A multidimensional questionnaire or scale has acceptable corrected item-total correlations ranging from 0.2 to 0.4 (Hobart & Cano, 2009). As a matter of fact, in this study, LT's Cronbach's alpha is close to 0.5. Thus, the internal consistency was low but acceptable (Taber, 2018).

Moreover, we decided to retain rather than omit items with low scores regarding LT's corrected item-total correlation (CITC), which ranges from 0.195 to 0.329. As Nunnally and Bernstein (1994) explained, although there are no firm rules for acceptable or desirable levels of discrimination, 0.30 is occasionally regarded as a minimum. This minimum can be reduced to 0.20 or 0.15 in low-stakes circumstances when other factors, such as LT, are likely to influence data quality. Generally, the greater the discrimination, the better. However, when correlations between item scores and construct scores exceed 0.90 and approach 1.00, it's important to question the item's distinctness from the construct, as overly strong correlations may be redundant and unnecessary.

The OL-MARS v.2 scales were validated with CFA, a widely used method for assessing construct validity (Swami et al., 2023), further bolstering their soundness. CFA can also examine the goodness-of-fit results of a scale's factor structure, providing a more precise and conclusive evaluation of latent variables (Soleimani et al., 2016) as cited in Groskurth et al. (2023) and Nikkhah et al. (2018). Since the structure of the scale is known a priori, we progress to checking the fit of an existing model using CFA (El-Den et al., 2020). In social and behavioral science research, researchers frequently use goodness-of-fit indices (GOFs) to assess the fit of latent variable models such as CFA (Groskurth et al., 2023). According to Goretzko et al. (2024), evaluating CFA model fit can be difficult since tests for exact model fit may focus on minor deviations, whereas fit indices cannot be fully assessed without identifying thresholds or cut-offs. This study found a GFI of 0.837, AGFI of 0.815, TLI of 0.709, NFI of 0.700, and RMSEA of 0.068, which indicates that the model with five subscales and two main constructs does not fully match all fit indices. According to Hu and Bentler (1999) as cited in Laar et al. (2021), "It is difficult to designate a specific cutoff value for each fit index because it does not [work] equally well with various conditions" (p. 27). Furthermore, Kenny (2024) warned that it is important to realize that a good-fitting model does not always imply validity. A "good-fitting" model is one in which all of the estimated parameters are not statistically different from zero. In contrast, a model with all statistically significant parameters may be a poor-fitting one. Models with illogical outputs (e.g., pathways with clearly the wrong sign), as well as models with low discriminant validity or Heywood cases, can be good-fitting. Parameter estimations must be carefully scrutinized to determine whether a model is plausible. It is also vital to understand that even if a model fits well, it is still feasible to improve it and eliminate specification flaws. Hence, having a well-fitting model does not imply that it is adequately described.

Jöreskog and Sorbom developed the GFI as an alternative to the chi-square test, which evaluates the proportion of variance explained by estimated population covariance (Tabachnick and Fidell, 2007, as cited in Hooper et al. (2008). The variances and covariances accounted for by the model show how well it replicates the observed covariance matrix. This statistic goes from 0 to 1; larger samples produce higher values. Traditionally, an omnibus cut-off point of 0.90 has been suggested for the GFI (Hooper et al., 2008).

The AGFI is adjusted based on degrees of freedom, with more saturated models resulting in poorer results. Like the GFI, the AGFI has values ranging from 0 to 1, with values of 0.90 or higher, often indicating well-fitting models. Given the generally negative influence of sample size on these two fit indices, they are not used as standalone indices; rather, because of their historical significance, they are widely used in covariance structure analyses (Hooper et al., 2008). Hu and Bentler (1999) as cited in Laar et al. (2021) stated that an AGFI value of 0.80 or greater indicates an acceptable fit.

The Non-Normed Fit Index (NNFI), often known as the Tucker-Lewis index (TLI), favors simple models. TLI is called non-normed because it can take values ranging from 0 to 1. Some offer a threshold of 0.80, however, Bentler and Hu (1999) suggest a NNFI $\geq$ 0.95. A TLI value of 1 indicates a perfect match. Hu and Bentler (1998, 1999) as cited in Prudon (2015) indicated an acceptable fit criterion of $\geq$ .95. The TLI reference values vary according to sample size and model complexity.

RMSEA measures how far the model deviates from the original model. This is a "badness of fit" test, with scores near "0" indicating the best match. RMSEA value below 0.05, indicating an excellent model fit. A value of 0.08 or lower suggests an adequate match; values more than 0.10 indicate a poor fit (MacCallum et al., 1996) as cited in Prudon (2015). Smaller values suggest a better fit. Hu and Bentler (1998, 1999) as cited in Prudon (2015) suggested a cutoff value of $\geq$ 0.06 for a suitable match. Therefore, an RMSEA of less than 0.06 is desired, but values as low as 0.08 are acceptable (Browne & Cudeck, 1993) as cited in Kyndt and Onghena (2014). However, Newsom (2023) warns that these criteria should not be set in stone, and there may be models that fall short of these goals for which no better options or theoretically feasible improvements appear to be possible.

Even though the GFI and TLI show a poor fit, we decided to present them as is. We did not apply the Akaike information criterion (AIC) as suggested by some researchers, including El-Den et al. (2020). However, as El-Den et al. (2020) also stated, "Not meeting these targets is not necessarily a reason to prevent authors or reviewers from publishing the results; however, when either the RMSEA is > 0.08 or the CFI and/or TLI is < 0.9, this is indicative of a very poor fit, and the results are unlikely to be generalizable." Likewise, Newsom (2023) noted that "It is not fair to change fit indices based on values that make your fit look better! As with any conventional cutoff recommendation, values tend to be taken overly seriously." Moreover, methodologists have advised that GOF cutoffs are (Groskurth et al., 2023). As Hooper et al. (2008) explain, while fit indices are useful, a structural model should be examined using substantive theory. Allowing model fit to drive the research process contradicts structural equation modeling's fundamental function of testing theories. Furthermore, in reality, fit indices can indicate a well-fitting model whereas individual model components may fit poorly.

The simulation by Groskurth et al. (2023) supports the conclusion that cutoffs cannot be simply applied to arbitrary analytical settings, and so fixed cutoffs are likely invalid in most cases. Their findings send a clear and simple message: GOFs' vulnerability to model misspecification varies significantly across simulated scenarios. Furthermore, GOFs are sensitive to a variety of data and analytical features. Their work emphasizes the fact that GOF values reflect more than just the size and proportion of model misspecification, and that GOFs respond to various data and analytic parameters in complex and unpredictable ways. As a result, one should not rely solely on GOF values to represent (mis) fit, let alone fixate on set cutoffs for model evaluation. We believe that this critical insight should be absorbed by all researchers who use CFA models, as well as included in statistics and methods curricula addressing model evaluation.

In addition, Wu (2017) used two second-order CFAs in a consolidated model to validate the OL-MARS v.2 scales. The results showed that the model did not fit the data due to the orthogonal relationship between the two higher-order components. This suggests that the awareness of one's attention problem is not directly associated with attention regulation. Thus, two separate second-order CFAs were fitted to the data, one for PAP and another for SRS. Both models showed an adequate fit. The authors of this study believe that Wus finding explains why certain of the test results for our model do not fit. However, we made no changes and did not proceed with two independent second-order CFAs. This could be a research project and opportunity for the future.

Table 6 shows that the factor loadings for items 6, 7, and 16 are lower than the others, with item 6 (0.199) being the lowest. Hair et al. (2013) provided standards for interpreting standardized factor loadings in practice. These are represented by the component coefficients for the main components, the factor matrix (for a single-factor or uncorrelated multiple-factor model), and the pattern matrix (for a correlated multiple-factor model). Thus, according to the table of loadings for practical significance (Hair et al., 1998), a factor loading cutoff of 0.30 is acceptable, with a sample size of 350 needed to attain significance (Hair et al., 2013) Hair et al., 2010, as cited in Ishak and Elgeka, 2023. Likewise, Cheung et al. (2024), CFA requires large samples (200 or more) to ensure reliable outcomes, so even a small standardized factor loading can be statistically significant. All items in each sub-dimension have factor loading values greater than 0.3, indicating a significant contribution to the corresponding factors.

Additionally, Rahn (2013) explains that for a variable to be considered significant, it should have a rotated factor loading of at least 0.4 (meaning > +.4 or ≤ -.4) on one factor. Some researchers apply even stricter criteria with a cut-off of 0.7. In some cases, this may not be feasible, such as when a researcher's analysis gives a highest loading of 0.5. Other researchers broaden the criteria by including variables with factor loadings of 0.2. Accordingly, the authors assume that the factor loading of 0.199 for item 6 seems acceptable.

The lesson to be gained from the preceding is that one should not be too quick to disregard information on ill fit simply because the unique variance is exceptionally small. That is not to say that signs of poor fit should never be dismissed as inconsequential (Prudon, 2015). As suggested by Andrade (2019), "All findings should be interpreted in the context of the study design, including the nature of the sample, the sample size, the reliability and validity of the instruments used, and the rigor with which the study was conducted" (p.214). Therefore, given the preceding findings, the Indonesian OL-MARS v.2 scale appears to be helpful for educators and researchers seeking to examine students' attention states while engaging in online learning aided by electronic devices that usually involve media multitasking. It will be a valuable instrument for Indonesian educators who wish to assess students' attention states and regulation techniques, which are closely related to ICT and media multitasking behavior.

Conclusion

The Online Learning Motivated Attention Regulatory Strategies (OL-MARS v.2) in Indonesian is a 24-item scale that measures adolescents' attention states and media multitasking behavior. The scale includes two major constructs: Perceived Attention Problems (PAP) and Self-Regulatory Strategies (SRS). This study adapted and provided sufficient proof of internal concistency, reliability, and validity for the Indonesian version of the OL-MARS v.2. The Indonesian translations of this instrument likewise have good internal consistency and have proven to be reliable and valid for assessing students' attention states and attention management strategies, especially among undergraduates who engage in media multitasking. Therefore, the study provides a reliable, validated, and easy-to-use instrument for future research, particularly among Indonesian university students.

Recommendation

This study might be considered a first step in research on the Indonesian version of the OL-MARS v.2. The results should be viewed with caution due to the sample being limited to one university and the lack of information about participant characteristics. Future research could include more Indonesian undergraduate and graduate students from various universities in other provinces or regions, as well as a closer look at differences in socioeconomic characteristics among students, since socioeconomic status can influence individual media multitasking behavior, which is linked to attention state and regulation strategies. Furthermore, this study has some limitations, such as the inclusion of only participants aged 16 to 23 years. This can have an impact on the generalizability of findings across age groups. The discovered two construct and five subscale model can still be evaluated and will require further study.

Declaration

Acknowledgments

The researchers would like to thank all undergraduate students at UKP, Surabaya for their voluntary participation in this study. We are grateful to Jiun-Yu Wu, Ph.D. for permitting this study's adaptation and use of the OL-MARS v.2 scale.

Funding

This study was funded independently, without help from any external party.

Authors' Contributions

The author, SG, designed and organized this research as a prerequisite for a dissertation proposal during her doctoral studies. SG also wrote the manuscript, organized the data collection, and analyzed the data. FDM supervised the statistical analysis process and reviewed the data processing. IH and CLR reviewed the writing of the manuscript and approved its final version.

Conflict of Interest

The authors disclose no conflicts related to this article's research, authorship, or publication.

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