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Assessing Media Multitasking Behavior in Academic Activities of Students at Hanoi University of Science and Technology: A Study Using the Media Multitasking-Revised (MMT-R) Scale

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Abstract

The rapid development of digital technology in modern life has led to the widespread emergence of media multitasking behaviour among university students, especially in high-tech learning environments such as Hanoi University of Science and Technology. This study uses the Media Multitasking-Revised (MMT-R) scale to assess the level of multitasking behaviour in the classroom among 257 students from various academic disciplines. The data were analysed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The theoretical model identifies two core behavioural constructs: Compulsive Phone Checking (CPC) and Media Distraction (MD). The results indicate that students tend to engage in multitasking at a moderate level, with no significant gender differences, suggesting that this behaviour is generational rather than gender specific. Furthermore, the intention to engage in multitasking is strongly associated with CPC - controlled device usage - while MD, which reflects passive and uncontrolled distraction, is no longer a significant predictor and may indicate signs of digital addiction. The findings suggest that the MMT-R scale can be used not only as a behavioural measurement tool but also as a screening and early diagnostic instrument to identify high-risk student groups. Based on this classification, students can be grouped to design appropriate interventions aimed at promoting more mindful use of digital devices in learning environments.

Keywords: Device usage behaviour, media distraction, media multitasking, technology addiction, university students.

1. Introduction

Engaging in activities beyond the scope of the lecture such as texting, browsing social media, or managing personal matters while listening to the instructor, has gradually become a “new norm” in university classrooms. This behavior is referred to as multitasking, defined as “the ability to perform multiple tasks simultaneously within a short period of time” [1] . This trend partly comes from the use of mobile devices to support learning. Phones and tablets make it easy to look up information instantly, take notes, interact through learning apps, and work together on the spot. It also shows how “mobile culture” is becoming more common in universities [2]. However, those very benefits also create opportunities for students to shift their attention to activities unrelated to learning, which disrupts concentration and negatively affects teaching and learning effectiveness.

Many studies have shown the harmful effects of multitasking on learning [3-6]. However, these studies have been conducted mainly in European countries and the United States, while media multitasking in the classroom is a complex phenomenon that depends on context, cultural characteristics, educational systems, and socio-economic conditions [4]. In Vietnam, this issue has begun to attract attention. However, existing studies mainly focus on examining the relationship between media multitasking and psychological or health-related problems, such as smartphone addiction (nomophobia), anxiety, or students’ sleep quality [7]. This gap leaves educational institutions without sufficient scientific evidence to develop specific policies or regulations regarding the use of mobile devices during class. Expanding research on multitasking behavior, particularly on the level of students’ multitasking in the classroom, therefore becomes an essential foundation for the development of appropriate guidelines and regulatory frameworks.

This study applies the Media Multitasking-Revised Scale (MMT-R) to measure the extent of media multitasking among students at Hanoi University of Science and Technology (HUST) during class sessions. The data collected and analyzed on students’ media multitasking behaviors in the classroom provide useful reference information for educational administrators and psychology practitioners in developing solutions to better support students in their university learning.

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The research focuses on identifying the level of students' media multitasking in class and the demographic factors influencing this behavior. Based on this foundation, the study seeks to address three main questions:

- Is the original structure of the MMT-R scale appropriate for assessing media multitasking behavior among students at a Vietnamese university of technology?

- To what extent do HUST students engage in media multitasking during class?

- How do demographic factors influence the level of multitasking behavior among the students who participated in the study?

The findings of this research not only shed light on the characteristics and context of this behavior within Vietnam's higher education environment but also offer practical value by providing essential data for developing appropriate policies on mobile device use. Furthermore, the results can assist lecturers in adjusting their teaching methods and in designing suitable pedagogical interventions to enhance learning outcomes and the overall quality of education.

2. Overview of the Research Problem

2.1. Structure and Manifestations of Media Multitasking Behavior in the Classroom

Media multitasking (MMT) behavior in the classroom is structured around two main components: active behaviors and passive tendencies. Active behaviors are often compulsive, reflected in students' continuous checking of their phones or texting even without a clear reason. Such behaviors usually stem from habits or from the fear of missing out on information (FOMO) [2]. In contrast, passive tendencies reflect situations in which students are distracted by factors beyond their control, such as notification sounds, auto-playing videos, or engaging content from their devices, which disrupt the learning process [6, 8]. These behaviors may occur even when learners have no clear intention, reflecting an increasing dependence on digital technologies in the educational environment.

Manifestations of media multitasking in the classroom are diverse. Many students frequently check and engage with social media platforms such as Facebook, Instagram, or Twitter during class, which disrupts their concentration [9]. Others develop the habit of watching entertainment videos on YouTube or TikTok during lectures, which interrupts the learning process and reduces learning effectiveness. According to van der Schuur, Baumgartner and Sumter [10], media multitasking behaviors, such as watching online videos while engaging in other activities, not only have negative effects on learning but are also associated with sleep disturbances, which indirectly influence academic outcomes. In addition, students often tend to open unrelated applications or websites, such as games, online shopping platforms, or news sites, while the lecturer is delivering the lesson.

Wu [3] showed that behaviors such as web browsing and the use of mobile applications in class reduce attention, impair memory, and comprehension, and thereby negatively affect academic performance.

2.2. The Media Multitasking Scale for Assessing Students' Media Multitasking Behavior in the Classroom

To assess media multitasking behavior in the context of university classrooms, this study employs the MMT-R, a shortened version consisting of 18 items measured on a 5-point Likert scale. This instrument was developed on a solid theoretical foundation and has been validated for reliability both theoretically and empirically in research on university students [11, 12]. The MMT-R scale has a two-factor structure, with items loading onto two groups that reflect either:

(1) (pro)active of compulsive, or inappropriate phone checking, for example, *"When talking to someone face to face, how often do you feel the urge to check your phone for unread messages, notifications, etc.?"*; or (2) more passive tendencies that encompass interference, distractibility, procrastination, and multitasking, for example, *"How often do you find yourself procrastinating by viewing media content online?"* The MMT-R items specifically measure the frequency of behaviors such as checking phones, texting, or browsing social media while engaged in other academic tasks.

Studies, particularly that of Ophir *et al.* [6], indicated that heavy media multitaskers (HMM) are more susceptible to attentional interference, have slower task-switching times (~0.3–0.4 seconds), and show reduced cognitive performance and memory. Subsequent studies have also agreed that, in educational contexts, media multitasking behaviors (such as texting or browsing social media during class) tend to impair concentration and academic achievement, for example, leading to lower GPAs.

In learning environments, media multitasking behaviors such as texting, browsing social media, or watching videos during class are associated with reduced attention and lower academic performance (for instance, lower GPAs). Students at HUST, who face high academic pressure and intensive technology use, are at greater risk of belonging to the heavy media multitasker (HMM) group.

The application of the MMT-R scale not only enables the classification of students according to their level of multitasking behavior but also allows for analysis of the relationship between multitasking levels and key cognitive indicators, including attentional control, task-switching speed and efficiency, and working memory. Based on these data, the study proposes educational interventions aimed at improving learning effectiveness and time management for university students in the digital age.

2.3. Factors Influencing Students' Media Multitasking Behavior in the Classroom.

Media multitasking (MMT) behavior in the classroom is influenced by various factors, both from the teaching environment and from students' individual characteristics.

First, the nature of the course plays an important role in triggering multitasking behavior. Courses that lack interactivity, have unengaging content, or rely on monotonous teaching methods often cause students to lose focus and become easily drawn into unrelated media activities. Aivaz and Teodorescu (2022) [12] found that the level of distraction increases significantly in both online and face-to-face classes when students perceive the lecture content as uninteresting or when active participation is not required.

Second, a loosely controlled and weakly monitored learning environment can facilitate the use of personal devices in class. In the absence of clear regulations or strict supervision, students can easily engage in MMT without fear of disruption or negative feedback from instructors [13].

Third, students' attitudes and perceptions toward technology also strongly influence their tendency to engage in MMT. If students believe that using phones, social media, or digital applications helps them entertain themselves, reduce boredom, or support their learning, they may underestimate or fail to fully recognize the negative impacts of MMT on the process of knowledge acquisition [9].

Fourth, the widespread availability of personal technologies, particularly smartphones and digital applications, has significantly increased access to media within the classroom. The portability, ease of use, and diverse functionalities of personal devices make multitasking behaviors more frequent and more difficult to control [7].

Finally, learning outcomes and effectiveness are also inversely related to MMT behavior. Students who frequently engage in media multitasking in the classroom often face difficulties in retaining information, engaging in deep processing, and completing academic tasks efficiently, which in turn affects their grades and overall learning quality [9].

3. Research Methodology

3.1. Research Methods

The study employs the MMT-R scale, consisting of 18 items measuring media multitasking behaviors, with two main components: active behaviors (such as frequent phone checking) and passive tendencies (caused by interruptions from multimedia use). The scale uses a 5-point Likert format and demonstrates high reliability (Cronbach's alpha equal 0.86), providing practical insights into the extent and habits of personal device use in learning.

The 18-item MMT-R scale is a shortened version developed by Lopez, Salinger, Heatherton, and Wagner (2018), who validated its construct validity in the context of research on social information processing. Subsequently, Lopez, Heatherton, and Wagner further applied the scale in studies on the relationship between media multitasking and health risks, thereby reaffirming the reliability and applicability of the MMT-R across different contexts [11].

3.2. Research Process and Organization

Step 1: Develop the theoretical framework and literature review. Analyze previous studies on multitasking behavior and the MMT-R scale.

Step 2: Construct the questionnaire, including sections on demographic information, multitasking levels, and TPB components. The instrument was developed based on scales that had been validated in international studies and adapted to fit the context of HUST students.

Step 3: Administer the questionnaire online and collect 257 valid responses from HUST students across different academic disciplines.

Step 4: Code the data using IBM SPSS Statistics, then check the reliability of the scale with Cronbach's alpha. Conduct exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to test the measurement model. Finally, perform descrsiptive statistics and normality tests for the Media Distraction (MD) and Constant Phone Checking (CPC) subscales of the MMT-R scale.

Step 5: Presenting and discussing the scientific and practical implications of the study

3.3. Criteria for Statistical Tests

To ensure reliability and statistical significance in data analysis, the study employs several common standards, including Cronbach's alpha, Pearson correlation, and linear regression testing.

Specifically, Cronbach's alpha is used to assess the reliability of the scale, with an acceptable threshold of 0.7 or higher [14].

In Pearson correlation testing, the correlation coefficient (r) is used to measure the strength and direction of the linear relationship between two quantitative variables. The value of r ranges from -1 to +1, where r greater than 0 indicates a positive relationship, r less than 0 indicates a negative relationship, and r equal 0 indicates no linear relationship. A correlation is considered statistically significant if the *Sig.* value is less than 0.05 [15, 16].

For EFA, the criteria include: KMO index greater or equal 0.6, Bartlett's Test with Sig. less than 0.05, factor loadings greater or equal 0.5, and total variance explained greater or equal 40% [17]. Confirmatory factor analysis (CFA) is then applied to test the goodness-of-fit of the measurement model. According to Hu and Bentler [18], acceptable fit indices including: chi-square/df less than 3, GFI greater 0.90, CFI greater 0.90, RMSEA less than 0.08, and PCLOSE greater 0.05 [18]. In addition, data normality is examined through Skewness and Kurtosis values. Variables with values within ±1 are considered approximately normally distributed [19], thereby meeting the conditions for parametric tests such as the t-test and linear regression.

Moreover, the independent samples t-test is used to compare the mean differences between two independent groups (e.g., male and female). For the test to be considered statistically significant, two conditions must be met: (1) the variances of the two groups must be equal, as tested by Levene's Test with *Sig.* greater 0.05, and (2) the Sig. (2-tailed) value of the t-test must be less than 0.05, indicating a statistically significant difference between the two groups [16]. If Levene's Test indicates unequal variances (*Sig.* less than 0.05), the result under "Equal variances not assumed" is used instead.

In addition to the statistical criteria above, the study also applies a classification rule for interpreting behavioral levels based on the value intervals of the 5-point Likert scale. Specifically, the interval value is determined by the formula:

$$\boldsymbol{Interval\,Value} = \frac{\boldsymbol{Maximum - Minimum}}{\boldsymbol{5}} = \mathbf{0.8} \quad (1)$$

Based on this, the scale is divided into five levels:

1. 1.00–1.80 (Never),
2. 1.81–2.60 (Rarely),
3. 2.61–3.40 (Sometimes),
4. 3.41–4.20 (Often),
5. 4.21–5.00 (Always).

This rule provides a consistent framework for interpreting the mean scores of multitasking behaviors, enabling a systematic, transparent, and quantitatively grounded assessment of the prevalence of each behavior among university students.

4. Results

4.1. Reliability Analysis of the Media Multitasking Scale – Revised

Table 1 presents detailed information on the two models included in the MMT-R. Specifically, the scale consists of the CPC - 6 items model and the Media Distraction (MD - 12 Items) model. The CPC model assesses the extent to which individuals feel compelled to check their smartphones frequently, while the MD model evaluates the degree of passive distraction caused by media use while performing other activities. The abbreviations of the models and the corresponding number of items are summarized below to facilitate the interpretation of subsequent analyses.

In addition, the results of internal consistency reliability testing were assessed using Cronbach's alpha and the minimum corrected item–total correlation. According to the standard set by Nunnally and Bernstein [14], a scale is considered reliable when Cronbach's alpha is greater or equal 0.7.

The results of the reliability analysis of the MMT-R components showed that both CPC and MD groups achieved Cronbach's alpha values exceeding 0.8, indicating high reliability and strong internal consistency among the observed items. However, within the MD group, one item yielded a negative item–total correlation (-0.115), which reduced the internal homogeneity of this factor. This suggests that participants' responses to this item tended to move in the opposite direction from their responses to other items within the same factor. Possible reasons include: (1) the item being phrased in reverse or in a confusing manner, (2) participants interpreting the item differently from its intended purpose, or (3) the item reflecting a distinct behavioral aspect not fully aligned with the factor structure.

As a result, this item reduced content homogeneity and lowered Cronbach's alpha. When the problematic item was removed, Cronbach's alpha increased from 0.895 to 0.905, indicating that the item had a considerable negative effect on overall reliability. This suggests that although the MD scale generally demonstrates high reliability, it is necessary to review and revise item content to ensure conceptual consistency.

Overall, these findings confirm that the MMT-R scale is an appropriate and reliable measurement tool in the study of media multitasking behavior, provided that the quality of individual items is carefully monitored

Table 1. Model information of the Models in the MMT-R

No.	Model	Abbreviation	N of Items	Cronbach's alpha	Min. Corr. Item-Total	Cronbach's Alpha if Item Deleted
1	Compulsive phone checking	CPC	6	0.883	0.502	0.851
2	Media Distraction	MD	12	0.895	-0.115	0.905

4.2. Description of the Survey Sample

In this study, sample size determination for EFA was based on practical statistical criteria. According to the classical rule of thumb, each observed variable requires a minimum of 5–10 participants [16]. With 18 items in the MMT-R scale, the recommended sample size thus falls between 90 and 180. In addition, MacCallum, Widaman, Zhang, and Hong [20] emphasized that sample size also depends on the level of communalities and the number of indicators loading on each factor (overdetermination). When the average communality reaches 0.40–0.50 and each factor has at least five observed variables, a sample size of 200–300 is considered sufficient to ensure stable solutions. The actual survey sample of this study was *N* equal 257, which not only meets these recommended thresholds but also achieves a KMO value of 0.939 and Bartlett's Test with *p* less than .001. According to Kaiser's [21] criteria, this result is rated as "marvelous," thereby confirming a high level of suitability for conducting EFA.

The analysis results presented in Table 2 provide a descriptive overview of the study sample. Among the 257 survey participants, 140 were male (54.5%) and 117 were female (45.5%), indicating a relatively balanced gender distribution.

Table 2. Summary of descriptive statistics for the research sample

Sample Characteristics		Frequency	Percentage (%)
Gender	Male	140	54.5%
	Female	117	45.5%
Year of study	1	67	26%
	2	84	33%
	3	70	27%
	4	25	10%
	5	8	3%
	7	3	1%

The majority of participants were second-year students (33%) and third-year students (27%), followed by first-year students (26%). Fourth- and fifth-year students accounted for smaller proportions, at 10% and 3% respectively. Overall, most participants were first- to third-year students (86%), representing a typical group that is in the stage of actively developing habits of technology use for both learning and entertainment - well aligned with the research context of media multitasking behavior.

4.3. Analysis of Gender Differences in the Level of Media Multitasking

The majority of participants were second-year students (33%) and third-year students (27%), followed by first-year students (26%). Fourth- and fifth-year students accounted for smaller proportions, at 10% and 3% respectively.

Beyond statistical significance, the study also examined effect sizes to evaluate the magnitude of practical differences. The mean multitasking score for male students ($M = 2.96$, $SD = 0.62$, $n = 140$) and female students ($M = 2.98$, $SD = 0.63$, $n = 117$) yielded Cohen's d approximately –0.025 (Hedges' g ≈ –0.025) and an effect size correlation of r approximately 0.013. These indices are all very small, consistent with the independent samples t-test result ($p = .841$), indicating that gender differences are practically negligible. With the current sample size, the minimum detectable effect (MDE) is approximately d approximately 0.35 at a 95% confidence level and power approximately 0.80.

To complement the t-test results, the study also calculated the effect size using Cohen's d. According to Cohen's [15] original definition, Cohen's d is computed as the mean difference divided by the pooled standard deviation of the two groups. For the present data (male: $M = 2.96$, $SD = 0.62$, $n = 140$; female: $M = 2.98$, $SD = 0.63$, $n = 117$), the result is Cohen's d approximately –0.025. This indicates an extremely small effect size, meaning that gender differences in multitasking behavior are practically negligible, which is consistent with the statistically non-significant t-test result ($p = 0.841$).

Table 3. Analysis of the difference in multitasking level between male and female students

		Levene's Test for equality of Variances		T-test for equality of Means						
		F	Sig.	T	Df	Sig.(2-tailed)	Mean difference	Std.Error difference	95% confidence interval of the difference	
									Lower	Upper
MMT (Media Multitasking)	Equal variances assumed	0.009	0.925	-0.201	255	0.841	-0.01576	0.07857	-0.17048	0.13896
	Equal variances not assumed			-0.200	245.005	0.841	-0.01576	0.07872	-0.17081	0.13929

Table 4. Comparison of differences in multitasking level between male and female

	Gender	N	Mean	Std. Deviation
MMT	Male	140	140	2.9606
	Female	117	117	2.9764

The difference in mean multitasking levels between male and female students is not statistically significant.

The Levene's test result (*Sig.* = 0.925 > 0.05) indicates that the variances between the two gender groups are homogeneous; therefore, the independent samples t-test was conducted under the assumption of equal variances. The Sig. (2-tailed) value of 0.841 which is greater than 0.05 shows that there is no statistically significant difference between male and female students in terms of their level of media multitasking in the classroom. The mean difference between the two groups (–0.01576) is very small, and the 95% confidence interval [–0.17048; 0.13896] includes zero, further confirming this similarity.

The descriptive statistics also reveal that the mean multitasking score of female students (M = 2.9764; SD = 0.63460) is nearly identical to that of male students (M = 2.9606; SD = 0.62099). The comparable standard deviations suggest that multitasking behavior is consistently maintained across the entire sample, regardless of gender.

These results indicate that multitasking in the classroom has become a widespread and uniform behavior across gender groups, reflecting a convergence in the learning practices of modern students. In a context where technology is ubiquitous and deeply integrated into student life, both male and female students engage regularly with digital devices and media platforms, leading to the formation of multitasking habits at comparable levels. This finding also suggests that multitasking behavior is no longer substantially influenced by biological characteristics such as gender but may instead arise from socio-technological factors, such as the design of the learning environment, connectivity pressures, or the pervasive presence of media tools in the classroom.

From this, it can be concluded that gender is not a determining factor in classroom multitasking behavior. Therefore, educational strategies or behavioral interventions should be designed in a universal manner, targeting the learning environment and behavioral control mechanisms rather than categorizing learners by gender.

4.4. Testing the Factor Analysis Model Assessing the Impact of Student Multitasking

4.4.1. Exploratory factor analysis of the Scale Structure

During the reliability testing and EFA, 5 out of the original 18 items (approximately 28%) were removed. The main reasons included: (1) corrected item–total correlations lower than 0.3 or negative values, indicating that the item was not conceptually consistent with the remaining items; (2) factor loadings less than 0.5 or cross-loadings on multiple factors, which distorted the structure; and (3) an increase in Cronbach's alpha when the item was removed, reflecting improved reliability. The elimination was based on statistical criteria and the principle of retaining the items that best represented the conceptual structure, thereby ensuring the validity and reliability of the scale.

Specifically, after reliability testing using Cronbach's alpha, from the original 18 items of the MMT-R scale, the research team removed the reverse-coded item MD7 due to its low item–total correlation and because the Alpha coefficient increased when the item was excluded. EFA was then conducted with the remaining 17 items to evaluate the underlying structure of the scale.

Table 5. Model summary of factors assessing the impact level of students' media multitasking

	Factor	
Code	1-MD	2-CPC
MD12	0.804	
MD11	0.767	
MD3	0.690	
MD9	0.650	
MD6	0.580	
MD5	0.561	
MD2	0.528	
MD10	0.514	
CPC1		0.764
CPC2		0.729
CPC3		0.722
CPC6		0.697
CPC4		0.590
KMO	*0.939*	
Cronbach's alpha	*0.905*	*0.833*
Total	*1.393*	
Cumulative %	*48.233*	

Results of data analysis from a survey of 257 student samples

The Kaiser-Meyer-Olkin (KMO = 0.939 > 0.6) and Bartlett's Test results (chi-square = 2115.701; Sig. = 0.000) indicated that the data were suitable for factor analysis. Using Principal Axis Factoring with Promax rotation, two factors with eigenvalues greater than 1 were extracted, with a cumulative variance explained of 48.233%. Although this level did not exceed the 50% threshold recommended by Hair *et al.* [17], it is still considered acceptable within the 40%–60% range for social science research [22]. This variance level is appropriate for the study of human behavior, which is inherently influenced by multiple external factors. Moreover, all retained items had factor loadings above 0.5 and Cronbach's alpha values greater than 0.8, indicating that both reliability and construct validity were maintained [17, 19]. We also noted in the study's limitations that this variance level should be further validated on larger samples or different populations to examine the stability of the model.

The results from the rotated factor loading matrix showed that 17 initial items were excluded because some variables had factor loadings below 0.5, cross-loaded onto two factors, or did not load onto any factor. After these items were removed, 13 variables remained and were distributed into two factor groups consistent with the original constructs of the MMT-R scale. These items were accurately loaded onto the two theoretical factors: CPC and MD, as proposed by Lopez *et al.* [11].

Specifically, the first factor group consisted of 8 items (MD12, MD11, MD3, MD9, MD6, MD5, MD2, and MD10), representing multitasking behaviors with psychological and behavioral impacts, with factor loadings ranging from 0.514 to 0.804. The second factor group consisted of 5 items (CPC1, CPC2, CPC3, CPC6, and CPC4), reflecting the perceptual/cognitive aspect of students' multitasking behavior, with factor loadings ranging from 0.590 to 0.764.

The Cronbach's alpha for the remaining 18 items was 0.901 (greater than 0.7), indicating that the excluded items did not contribute meaningfully to the reliability of the MMT-R scale. Overall, the EFA results demonstrate that the two-factor scale structure possesses satisfactory validity and reliability for subsequent analyses.

4.4.2. Measurement model testing through confirmatory factor analysis: assessing model fit and factor loadings

To identify the latent structures of students' media multitasking behavior, the research team conducted an EFA. The results showed that the scale was divided into two main factors: MD and CPC, with all observed variables achieving factor loadings greater than 0.5, confirming internal consistency within each behavioral group.

Subsequently, the model was re-examined using CFA. Fit indices such as chi-square/df = 2.049, GFI equal 0.926, CFI equal 0.952, and RMSEA equal 0.064 indicated that the two-factor model demonstrated good fit with the survey data. This finding reinforces the EFA results and further validates that the scale structure accurately reflects the characteristics of students' multitasking behavior in the modern educational context, as illustrated in Fig. 1.

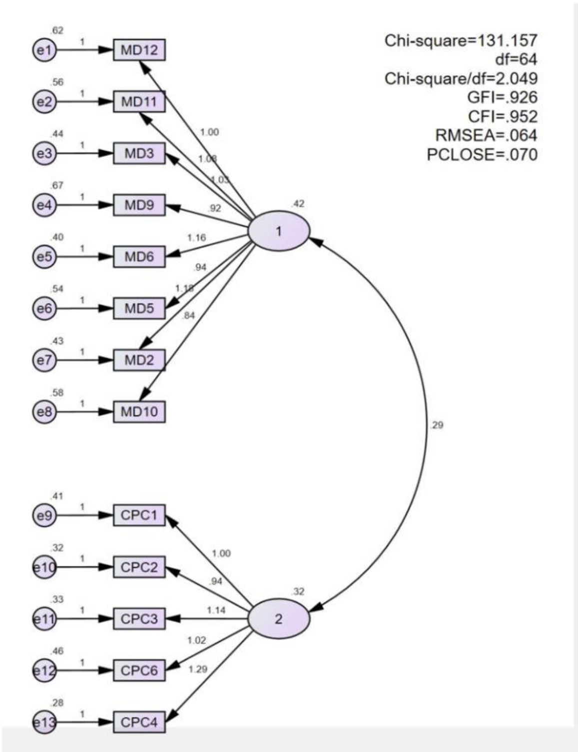

Fig. 1. CFA model based on the analysis results

The division into two factor groups: active behaviors (CPC) and passive behaviors (MD), also suggests a classification approach to learners based on their level of control over multitasking behaviors. MD represents reactions to environmental stimuli, while CPC reflects a proactive tendency to use devices, potentially driven by habit or intrinsic needs. These results highlight that students' multitasking behavior is not merely random but has a distinct psychological structure that can be identified through patterns of media use.

Thus, through the combined EFA and CFA analyses, the study established a two-factor model that captures the distinctive features of media multitasking behavior, while also providing a solid foundation for developing targeted intervention strategies in future applied research.

4.5. Level of Multitasking Behavior

Table 6 presents the descriptive statistics and normality indicators for the MMT-R scale and its two subscales, MD and CPC

Table 6. Normal distribution of the MMT-R scal

Model	N	Min	Max	Mean	Std. Deviation	Skewness		Kurtosis	
MD	257	1.00	5.00	2.7247	0.71353	0.097	0.152	0.313	0.303
CPC	257	1.00	5.00	3.2109	0.66793	-0.304	0.152	0.673	0.303
MMT	257	1.06	5.00	2.9678	0.62604	-0.012	0.152	0.938	0.303

Descriptive analysis shows that the overall mean score of the MMT-R scale is 2.9678 (*SD* = 0.62604), approaching the upper bound of the "sometimes" category. This indicates that multitasking is no longer a rare occurrence in the classroom but is gradually becoming a common reflex among modern students.

Within this, active behavior (CPC) is more prominent than passive behavior (MD). The mean score of CPC (*M* = 3.2109) suggests that many students are not merely distracted but actively and repeatedly use their phones during class as a habit shaped by intrinsic motivations, such as updating information, engaging in social interaction, or regulating emotions. This implies that multitasking is no longer just a passive response to the technological environment but has become a purposeful and stable behavior, reflecting the integration of technology into students' personal learning experiences.

By contrast, the MD factor has a lower mean score (*M* = 2.7247), but its higher standard deviation (*SD* = 0.71353) indicates that some students remain strongly affected by distractions such as sounds, notifications, or digital content outside the lecture. This dispersion suggests that students' ability to self-regulate under the influence of the digital environment is uneven and may be linked to differences in attentional capacity, learning cognition, or personal device management skills.

Moreover, MD shows the highest standard deviation among the three components (*SD* = 0.71353), highlighting significant variability across individuals. This suggests the presence of two distinct groups: those who can effectively control their learning environment and those who are more vulnerable to media-related distractions (e.g., sounds, notifications, and applications). Such divergence implies that categorizing students based on their susceptibility to the digital environment is necessary when designing learning support interventions.

In terms of distribution, all three variables have skewness and kurtosis values within the ±1 range, indicating that the data approximate a normal distribution. However, CPC shows a negative skewness (–0.304), reflecting a tendency among some students to check their phones at levels above the mean, which may signal compulsive, repetitive behavior. Meanwhile, MD has the lowest kurtosis (0.313), suggesting greater dispersion and the presence of more extreme values compared to the other factors. This is consistent with the reality that distractions often arise unexpectedly and uncontrollably, leading to wide variations in students' responses.

Overall, the results indicate that students' multitasking behaviors in the classroom are not homogeneous but rather stratified: one group engages in intentional, purposeful multitasking, while the other is more influenced by passive stimuli. This behavioral stratification highlights the need for tailored learning support interventions, such as psychological counseling for the passive group or training in device management skills for the active group.

5. Conclusion

The study explored students' media multitasking (MMT) behavior in the classroom from a quantitative perspective, employing the MMT-R scale along with statistical analyses such as EFA, CFA, t-tests, and regression. The results indicate that multitasking is no longer an occasional phenomenon but is gradually becoming a common learning reflex in modern higher education settings.

Specifically, the mean score of the MMT-R scale was 2.9678, approaching the "sometimes–often" range, reflecting a medium-to-high level of multitasking. Within this, CPC was more prominent, with a mean score of 3.2109, approaching the "often" category. This suggests that most students engage in purposeful phone-checking as a habitual behavior, not only for entertainment but also as a way to regulate emotions or fill cognitive gaps.

By contrast, MD, which reflects passive distraction from the digital environment, had a lower mean score (*M* = 2.7247), but a higher standard deviation, indicating a clear differentiation among students: some demonstrated strong self-control, while others were easily influenced by notifications, sounds, or irrelevant digital content. This highlights that multitasking manifests in two dimensions, active and passive, with varying levels of behavioral control across individuals.

Particular attention should be directed to the passive group, which may be at risk of media dependency. Additional assessments are needed to determine whether these students are vulnerable to media addiction, thereby enabling timely and targeted interventions.

Furthermore, the t-test results confirmed that there were no significant gender differences in multitasking behavior, indicating that the phenomenon is generational rather than biological. This suggests that educational interventions should be designed according to behavior type and intensity, rather than grouping students by gender.

Factor analysis also demonstrated that the two-component structure (CPC and MD) of the MMT-R scale was firmly established through both EFA and CFA, reinforcing the theoretical foundation for developing strategies to classify students based on their level of multitasking control.

Overall, the study sheds light on a subtle but consequential trend: students are increasingly accumulating technology multitasking habits in the classroom, and this tendency is more intentional than incidental. This underscores the need for intervention strategies that go beyond prohibition, focusing instead on fostering self-awareness, device management skills, and stratified interventions. Such approaches are essential to safeguard concentration and sustain learning effectiveness in the context of digital education.

With comprehensive adjustments to address the limitations in analysis and strengthen the validity of the scale, this study promises to make valuable contributions to a deeper understanding of media multitasking behavior in the context of higher education in Vietnam. The immediate priority is to refine the core analyses; subsequently, methodological and technical improvements will be implemented to enhance the reliability and practical applicability of the findings. Overall, this study can offer meaningful and practical contributions to expanding knowledge of media multitasking in Vietnamese higher education.

6. Limitations

Although the EFA results in this study indicated that the MMT-R scale has a clear two-factor structure and meets statistical reliability criteria (KMO = 0.939; Cronbach's alpha > 0.8), researchers should continue to thoroughly examine the items in future applications. Specifically, several items were removed for failing to meet the required thresholds of factor loadings (factor loading < 0.5), low communalities, or cross-loadings on multiple factors. This raises the need to review the conceptual structure of each item to ensure accuracy and appropriateness across different application contexts. Therefore, to maintain the stability and applicability of the scale in varying contexts, particularly when applied to different samples or at different times, revalidation of internal consistency and factor structure is required. Such efforts will help preserve the accuracy and measurement validity of the MMT-R in research on students' media multitasking behavior.

The analysis of cumulative variance explained reached 48.233%, while this does not exceed the 50% threshold recommended by Hair *et al.* [17], it still falls within the acceptable range of 40–60% for social science studies [22]. Nonetheless, this level of variance should be confirmed in future studies with larger samples or different populations to examine the stability of the factor model.

The study employed convenience sampling with voluntary participation via an online questionnaire. Although this approach is efficient and enables access to multiple schools and departments, it carries the risk of sampling bias and limits the representativeness of the data, thereby constraining the generalizability of the findings to the broader student population.

Moreover, the study was conducted at a technical university in Vietnam, which further restricts the extent to which the results can be generalized to students in other disciplines or geographic regions. Future research should therefore revalidate the MMT-R factor structure using more advanced techniques such as multi-group CFA, and integrate both quantitative and qualitative data to gain deeper insights into how students interpret and respond to individual items. In addition, testing the stability of the scale over time will be crucial to ensuring reliability in long-term applications.

Furthermore, the authors recommend extending future research toward experimental designs to evaluate the effectiveness of behavioral interventions for media multitasking in classroom environments. For instance, experimental models could incorporate technologies such as AI-enabled cameras or motion sensors to detect inattentive behavior, or implement psychological and behavioral support programs for students who are highly prone to distraction. Controlled experimental trials would allow for testing the impact of such interventions on students' actual learning behaviors, thereby providing practical evidence for educational policies and informing the long-term applicability of the MMT-R scale.

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Appendix A. Scale and Coding

Scale	Code	Item Content	Source
Compulsive Phone Checking	CPC1	You often use your phone for entertainment (e.g., watching videos, playing games) during class.	Lopez *et al.* , 2019
	CPC2	During class, you tend to check your phone for messages or notifications.	Lopez *et al.* , 2019
	CPC3	You tend to procrastinate in class by watching videos or using social media.	Lopez *et al.* , 2019
	CPC4	In class, you often switch from listening to the lecture to doing something else (e.g., browsing the web, writing unrelated notes) without completing the initial task.	Lopez *et al.* , 2019
	CPC5	You tend to use multiple devices/apps simultaneously during class (e.g., using your phone while working on a laptop).	Lopez *et al.* , 2019
	CPC6	You frequently text or reply to messages during class.	Lopez *et al.* , 2019
MD	MD1	You feel the need to check messages or emails even during class.	Lopez *et al.* , 2019
	MD2	You are distracted by notifications appearing on your phone while studying.	Lopez *et al.* , 2019
	MD3	While in group discussions or lectures, you are easily distracted by surrounding sounds or behaviors.	Lopez *et al.* , 2019
	MD4	If you receive a notification during a lecture, you tend to check your phone immediately.	Lopez *et al.* , 2019
	MD5	While studying, you are distracted by thoughts of what you plan to do after class.	Lopez *et al.* , 2019
	MD6	Notifications from your phone affect your ability to concentrate in class.	Lopez *et al.* , 2019
	MD7	When starting to study in class, you can maintain focus well. [R]	Lopez *et al.* , 2019
	MD8	You tend to check your phone even when concentrating, just out of curiosity or fear of missing out.	Lopez *et al.* , 2019
	MD9	While talking directly with classmates or instructors, you feel the urge to check your phone.	Lopez *et al.* , 2019
	MD10	Using your phone/laptop in class for non-academic purposes affects your learning effectiveness.	Lopez *et al.* , 2019
	MD11	You think that your friends or instructors perceive you as easily distracted during class.	Lopez *et al.* , 2019
	MD12	In class, you are influenced by others’ use of electronic devices.	Lopez *et al.* , 2019