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The Interplay of Digital Distraction Dimensions and the Efficacy of Online Counseling for MOOC Learners: A Moderation Analysis

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Abstract

This study highlights the concentration barriers experienced by Massive Open Online Course (MOOC) participants due to the many digital distractions in distance learning. To address this problem, a quantitative study was conducted on 43 civil servant respondents using statistical analysis through Jamovi and Python software to map the relationship between the level of interference and the demographic profile of the participants. The results of the study showed that interventions through online psychological counseling were effective in significantly reducing cognitive impairment. These findings make an important contribution to the development of a more optimal self-regulated learning strategy in the online education ecosystem. This innovative methodology offers a promising avenue for future research, allowing the development of personalized and inclusive online learning strategies while maintaining high levels of performance, reaching an average predictive impact on distraction reduction primarily driven by the mitigation of procrastination habits for all demographic scenarios, as age, gender, and education levels were found to have no significant moderating effect.

Keywords: Cognitive Interference, Online Education, Procrastination, Psychological, Quantitative Analysis, Self-regulated Learning.

Introduction

Education through Massive Open Oline Courses (MOOCs) is rapidly (1) evolving into a means of learning that is easily accessible to a global audience (2). These MOOCs are the best means that can reach areas where there is no education in general (3). However, the learning process through these MOOCs is often hampered by digital distractions that cause negative impacts on learning concentration, motivation, and academic achievement (4, 5). In response to this condition, psychological counseling is present as a solution to improve self-regulation (6) and self-focus management skills (7). Along with the development of today's technology in the field of communication, online counseling through video, chat and email can be a practical and economical alternative (8). Various early studies have shown that interventions through online counseling are able to equip students with self-management skills to minimize digital distractions (9) and optimize the quality of their learning experience (8, 10, 11). Although various studies have confirmed the negative impact of digital distractions as well as the potential benefits of online psychological counseling (9, 12), there are limitations in the current literature that need to be bridged. Previous research has tended to measure digital distractions in general (13, 14), without distinguishing between specific types of distractions. As a result, it is not known exactly which type of digital distraction most significantly affects academic concentration and performance in the Massive Open Online Courses (MOOC) environment. In addition, the effectiveness of online psychological counseling as an intervention to mitigate digital distractions in MOOC learning, as well as the factors underlying the success of these interventions, is still minimally explored (13, 14). Several points discussed imply a research gap exists in the lack of a comprehensive understanding of the

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specific types of digital distractions that most strongly hinder the learning process in MOOC learning. in MOOC learning. Previous research has not specifically investigated the interaction between types of digital distractions, online psychological counseling, and demographic factors within the context of MOOC learning (15, 16). While previous studies have extensively explored digital distraction in academic settings, this research offers a unique contribution by examining the interplay between specific distraction dimensions—such as procrastination and gaming—within the context of professional learners (Civil Servants) in a MOOC environment. This study investigates a novel approach by integrating targeted online psychological counseling specifically designed to address these various subtypes of digital distraction, filling the gap in built-in behavioral management support within MOOC platforms.

This research is important, because it explores the use of online psychological counseling as a practical and affordable solution to overcome the barriers of digital distractions experienced by students in learning MOOCs (17). This study not only evaluates the success of the interventions carried out, but also examines the influence of demographic factors such as gender, age, and education level (9) on the phenomenon of digital distractions. The purpose of the analysis of these variables is to gain a deeper understanding of the phenomenon, so that the results of the research can be a practical basis in designing more targeted and effective intervention strategies for adult learners (18, 19).

This study investigates the impact of online psychological counseling on digital distraction among students engaged in MOOCs. Specifically, the research addresses the following objectives:

(a) To determine the pattern of interrelationships between the different dimensions of digital distraction experienced by students while learning through MOOCs following psychological counselling,

(b) To identify which type of digital distraction serves as the most significant predictor of the total reduction in distraction during MOOC-based learning following online psychological counselling,

(c) To evaluate whether demographic factors specifically gender, age, and education level moderate the effect of online psychological counseling on the reduction of digital distractions.

This research aims to update and strengthen the relevance of Self-Regulated Learning (SRL) theory in order to address the challenges of learning in a digital environment, especially in Massive Open Online Courses (MOOCs) that demand high independence. The main focus is to fill the gaps in the literature regarding how online psychological interventions can change students' cognitive processes in managing digital distractions while learning. In addition, by examining the influence of demographic background on the effectiveness of counseling, this study seeks to provide a deeper understanding of the different intervention needs for each individual, so that existing theoretical models can adapt to the real needs of the distance education era.

Methodology

The study employed a quantitative research method with a correlational design. This approach was selected to objectively measure the relationships among variables, identify the primary predictors of reduced digital distraction, and examine the moderating effects of demographic factors on the effectiveness of the intervention.

Participants

This study involved 43 respondents who were selected through purposive sampling with the criteria of civil servants in Central Java who are actively participating in online training based on Massive Open Online Courses (MOOCs). To validate the adequacy of the sample, a post-hoc power analysis was performed using G*Power software, which showed that the sum $n = 43$ reached a statistical strength of 0.80 to detect a large effect size ($f^2 = 0.35$) at a significance level of $\alpha = 0.05$. Although the sample size was recognized as a limitation of the study, the size was considered adequate for the initial exploratory analysis of the phenomenon of digital distraction (20) and statistically sufficient to identify a significant relationship between the digital distraction dimension and the outcome of the intervention.

Data Collection Techniques

Data were gathered using a non-test approach via a 40-item questionnaire based on a 1–4 interval scale to assess the level of digital distraction. The intervention's effectiveness was evaluated by calculating the variance between pre- and post-intervention scores; specifically, improvement was indicated by a reduction in participants' total scores following the counseling session. The instrument encompasses eight dimensions of digital distraction: computer gaming, entertainment video consumption, duration of social media usage, access to non-educational websites, exposure to irrelevant content (21), digital addiction, emotional disturbances, and procrastination-related distractions (7). Furthermore, demographic information, including gender, age, and education level, was collected to support subsequent moderation analysis.

Validity and Reliability of Instruments

The validity of the research instrument was assessed using content validity and analyzed with the Pearson product-moment correlation coefficient as shown in Table 1. Instrument reliability was assessed using Cronbach's Alpha. The results of the validity and reliability tests are presented below:

Table 1: Validity and Reliability Statistics for the Digital Distraction Scale

Instrument	Item Total	Invalid	Valid	Cronbach's α
Digital Distraction	40	0	40	0.897

Note: Cronbach's α indicates the reliability coefficient of the instrument; values above 0.70 indicate acceptable internal consistency. N = 40 items.

Table 1 presents an analysis of the reliability of research instruments that measure the "Digital Distraction" variable. Based on this data, it can be explained that this instrument consists of a total of 40 statement items that are all declared valid (40 items), so that no items are considered invalid (0). The value of Cronbach's Alpha obtained is 0.897. This figure indicates that the instrument has a very high level of reliability (because it is above 0.70 or 0.80), which means that the measuring tool is consistent and reliable in measuring the digital interference variables studied.

Data Analysis

Methodological steps in this quantitative study that uses Jamovi and Python software to analyze the data. The analysis stage begins with the application of descriptive statistics and data visualization to understand the characteristics and distribution of the variables being studied (such as histograms and boxplots). Furthermore, this study uses the Pearson correlation test to measure the closeness of the relationship between dimensions in the digital distraction variable, which is then followed by regression analysis to determine which dimension is most influential in predicting the decrease in the level of distraction. As a final stage, a moderation analysis was conducted to evaluate the extent to which demographic variables, such as gender, age, and education level, affect the effectiveness of the intervention provided.

Results

The Pattern of Interrelationships between the Different Dimensions of Digital Distraction during Learning with MOOCs

The distribution of the research data across the various dimensions of digital distraction is presented to ensure the consistency of the sample size used in the analysis. Table 2 summarizes the total count of respondents for each specific aspect of distraction, confirming that 43 participants were consistently recorded across all categories.

Table 2: Digital Distractions during MOOC

Aspect	Playing Computer Games	Entertainment Video	Social Media	Unwanted Websites	Unwanted Videos	Emotional	Digital Addiction	Procrastination	Total
count	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0
mean	51.907	51.349	51.628	51.907	28.605	29.302	30.0	28.605	28.884
std	21.865	21.96	21.992	21.865	12.456	12.798	12.536	12.646	12.024
min	36.0	36.0	36.0	36.0	20.0	20.0	20.0	20.0	20.0
25%	36.0	36.0	36.0	36.0	20.0	20.0	20.0	20.0	20.0
50%	36.0	36.0	36.0	36.0	20.0	20.0	20.0	20.0	22.0
75%	72.0	72.0	72.0	72.0	40.0	40.0	40.0	40.0	39.0
max	144.0	144.0	144.0	144.0	80.0	80.0	80.0	80.0	80.0

Note: Std. Deviation = Standard Deviation; Count represents the number of respondents included in the analysis (N = 43). Descriptive statistics were calculated for each aspect of digital distraction.

Table 2 presents a descriptive statistical analysis of nine aspects related to digital media use behavior, namely playing computer games, watching entertainment videos, social media, unwanted websites, unwanted videos, emotional aspects, digital addiction, procrastination, and overall totals. This data involved 43 respondents for each aspect. In general, the results of the analysis showed a grouping of value patterns: aspects of gaming, entertainment videos, social media, and unwanted websites had higher mean values, ranging from 51.3 to 51.9, compared to the aspects of unwanted video, emotional, digital addiction, procrastination, and total, which averaged between 28.6 and 30.0. The considerable standard deviation, especially in the first four aspects (around 21.8), showed a fairly wide variation in answers among respondents. In addition, the median score (50%) of 36 for the first group and 20 for the second group, as well as a uniform minimum, indicates that the data has a distribution that tends to be asymmetrical and concentrated on certain scores before jumping to a maximum score of 144 or 80.

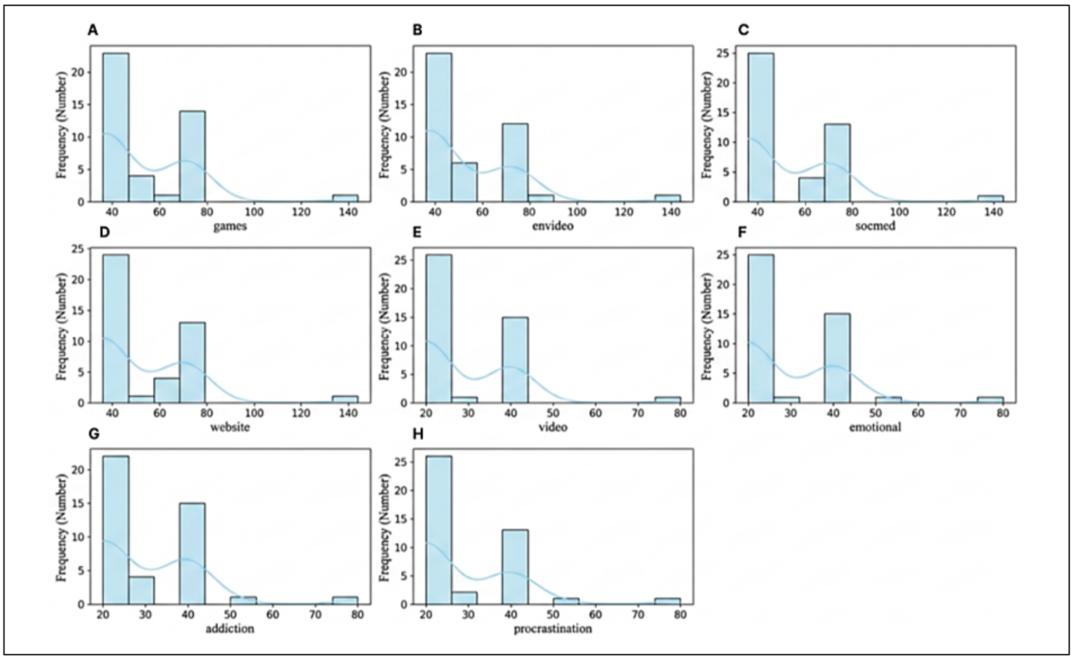

Figure 1: Distribution of Digital Distraction Variables. (A) Games, (B) Envideo, (C) Social Media, (D) Website, (E) Video, (F) Emotional, 9G) Addiction, (H) Procrastination

Figure 1 shows a set of eight histograms (Figures 1A-1H) equipped with a density plot, which aims to illustrate the frequency distribution of numerical data related to respondents' digital and psychological behavior. Each graph represents a different variable, namely games, envideo (video entertainment), socmed (social media), website, video, emotional, addiction, and procrastination (procrastination). In general, the distribution pattern on all charts tends to be bimodal or not normally distributed, where there are two dominant data groups: one large group with low values (located on the left side of the chart) and a smaller secondary group with moderate values (in the middle of the chart). In addition, there was an outlier or outlier in the extreme right value on almost all charts, which showed that a small percentage of respondents had a much higher score than the majority of other respondents.

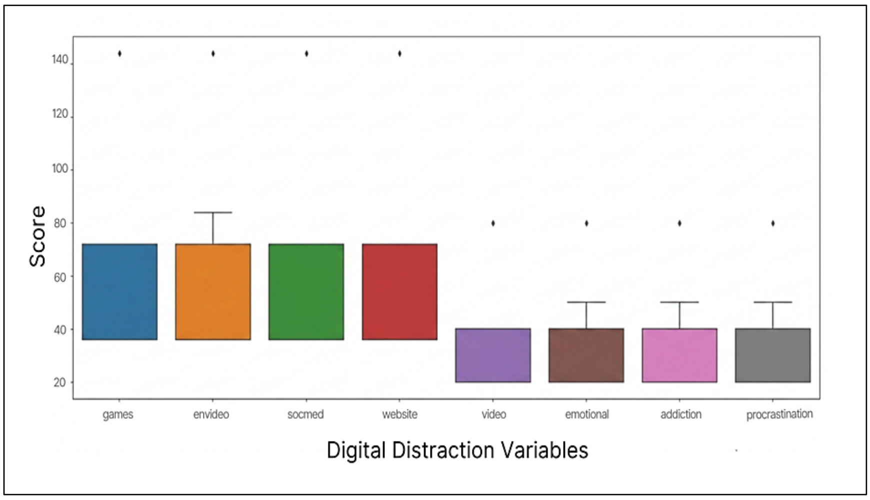

Figure 2: Boxplot Variable Digital Distraction

Figure 2 visualizes the score distribution of eight variables related to digital distraction. Overall, the data was divided into two main groups based on their score rate: the first group (games, envideo, socmed, website) had a higher median score (about 70), while the second group (video, emotional, addiction, procrastination) had a lower median (about 40). The envideo variable has a wider interquartile range than the other variables, indicating a greater variation of data in the category. In addition, each variable indicates an outlier (outlier data point) that is far above the normal score range, with the outlier value for the first group reaching a score above 140, while for the second group it is at 80. Statistically, this graph shows that respondents tend to score higher on aspects of digital platform use such as gaming and social media compared to specific psychological or behavioral aspects such as addiction and procrastination.

Correlation between Aspects of Digital Distraction after Online Counseling during Learning with MOOCs

An analysis of the relationships between various digital distraction dimensions was conducted to identify how these aspects interconnect following the intervention. Figure 3 shows the correlation heatmap, which provides a clear visual representation of the strength and direction of the associations among the different distraction variables.

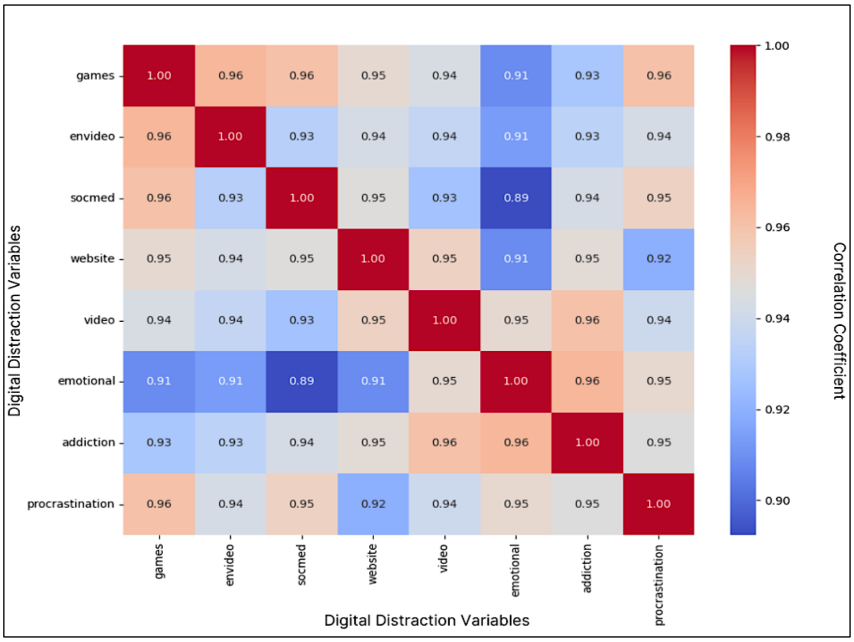

Figure 3: Correlation Heatmap Among Digital Distraction Aspects

Figure 3 is a correlation matrix (correlation heatmap) that shows the statistical relationships between various variables related to digital distraction. The numbers inside each cell represent a correlation coefficient that ranges from 0.90 to 1.00, which indicates that all the variables in this graph have a very strong positive correlation rate with each other. The closer the dark red color, the stronger the correlation between the variables, while the blue color shows a relatively “lower” correlation but remains in a very high range.

Specifically, this matrix analyzes variables such as games, envideo (possibly entertainment video), socmed (social media), website, video, emotional, addiction, and procrastination. Since all correlation coefficients are above 0.89, it can be concluded that there is a very close linear relationship between the use of these digital media and emotional factors, addiction levels, and procrastination behaviors. For example, the variables addiction and emotional have a very high correlation (0.96), which indicates that an increase in one variable is likely to be followed by a significant increase in the other. Overall, this image visualizes how different forms of digital distraction are closely intertwined in shaping a person's behavior.

Which type of Digital Distraction is the Strongest Predictor of Overall Distraction Reduction Following Psychological Counseling

This analysis investigates which types of digital distractions are most significantly predictive of overall distress reduction during Massive Open Online Course (MOOC) learning, following psychological counseling.

Table 3: Predictors of Digital Distraction Reduction

Predictor	Estimate	SE	t	p
Intercept	171.649	37.29	4.603	<.001
Watching entertainment videos	-1.014	1.81	-0.561	0.579
Time spent in social media	2.947	1.96	1.502	0.142
Visiting websites unrelated to learning	-4.022	1.97	-2.046	0.048
Watching unwanted videos	4.111	2.84	1.449	0.156
Digital addiction	0.667	2.98	0.224	0.824
Distraction by procrastination	-9.201	2.90	-3.176	0.003
playing computer games	-5.177	2.50	-2.068	0.046

Note: SE = Standard Error; t = t-statistic; p = p-value. $p < 0.05$ indicates statistical significance. Negative estimates indicate an inverse relationship between the predictor and the dependent variable.

The results of the analysis in Table 3 show that the tendency to procrastinate is the main factor that has the most influence on reducing digital distraction (Estimate = -9.201, $p < 0.003$). These findings indicate that during the counseling process, these tendencies contribute most significantly to the reduction of digital distractions. In addition, irrelevant website visits (Estimate = -4.022, $p = 0.048$) and the duration of playing computer games (Estimate = -5.177, $p = 0.046$) were also shown to have a negative influence on digital distractions, albeit with a lower impact. Overall, it can be concluded that visiting websites that are not related to learning materials and playing computer games play an important role in suppressing digital distractions after psychological counseling. On the other hand, variables such as the duration of social media use, watching entertainment videos, and the level of digital addiction did not have a significant association with the reduction of these distractions ($p > 0.05$). An intercept value of 171.649 indicates a baseline distraction reduction rate that already exists before other predictor variables are taken into account. Therefore, the most effective main step to reduce the overall level of distraction is to pay special attention to improving procrastination, restricting access to irrelevant websites, and regulating the length of time spent playing computer games.

Impact of Demographics on Counseling Effectiveness

The results of the analysis of the influence of gender on the effectiveness of counseling in reducing digital disturbance are presented in the following Table.

Table 4: Moderation Analysis of Gender on Digital Distraction Reduction

Predictor	Estimate	SE	95% Confidence Interval		t	p
			Lower	Upper		
Intercept[a]	91.490	14.71	84.10	105.90	6.218	<.001
Gender ✻ Hours spent on playing computer games:						
Female – Male	-0.505	1.42	-2.38	3.39	-0.354	0.725
Gender ✻ Distraction by procrastination:						
Female – Male	0.655	2.05	-3.49	4.80	0.320	0.751
Gender ✻ Visiting websites unrelated to learning:						
Female – Male	0.477	1.29	-2.13	3.09	0.370	0.713

Note: SE = Standard Error; CI = Confidence Interval; t = t-statistic; p = p-value. p < 0.05 indicates statistical significance. [a]Intercept represents the baseline value of the regression model. Gender interaction terms compare female respondents relative to male respondents.

The results of the moderation analysis presented in Table 4 show that the gender of students does not affect the effectiveness of psychological counseling in reducing digital distractions. The interaction between gender and gaming duration was found to be insignificant (b = -0.505, p = 0.725), indicating that the reduction in distraction was universally applicable to all genders. Similar results were also found regarding the interaction between sex and distraction due to procrastination (b = 0.655, p = 0.751), which proves that the impact of online counseling in overcoming procrastination does not depend on the student's gender. Finally, the analysis of the influence of gender on visits to sites that were not related to learning also showed no significant interaction, with a significance value of 0.713. This confirms that the impact of site visits on counseling outcomes is the same for male and female students, which is reinforced by the 95% confidence interval data in Table 4, which shows a range of insignificant effects.

Conversely, the moderation analysis regarding the demographic factor of age revealed the following results concerning its influence on the effectiveness of online counseling in reducing digital distractions:

Table 5: Moderation Analysis of Age on Digital Distraction Reduction

Predictor	Estimate	SE	95% Confidence Interval		t	p
			Lower	Upper		
Intercept[a]	102.656	10.76	81.25	101.19	9.538	<.001
Age ✻ Hours spent on playing computer games:						
(35-44) – (25–34)	1.159	1.14	-3.47	1.15	1.015	0.317
(45-54) – (25–34)	-1.307	1.79	-2.31	4.93	-0.732	0.469
Age ✻ Visiting websites unrelated to learning:						
(35-44) – (25–34)	-1.397	1.14	-3.72	0.921	-1.221	0.230
(45-54) – (25–34)	0.758	1.68	-2.65	4.166	0.450	0.655
Age ✻Distraction by procrastination						
(35-44) – (25–34)	-0.912	1.70	-4.35	2.52	-0.538	0.594
(45-54) – (25–34)	1.434	2.77	-4.18	7.05	0.517	0.608

Not**e**: SE = Standard Error; CI = Confidence Interval; t = t-statistic; p = p-value. p < 0.05 indicates statistical significance. [a]Intercept represents the baseline value of the regression model. Gender interaction terms compare female respondents relative to male respondents.

Table 5 presents an analysis of the role of demographic variables, namely age, on the effectiveness of online counseling in reducing digital distractions. The findings of the study indicate that there is no significant interaction between the age factor and the duration of use of computer games. This is supported by the significance of the interaction between the duration of playing games with the age groups of 35–44 years and 45–54 years and the comparison group (age 25–34 years), which was above the threshold of 0.05 (p = 0.317 and p = 0.469, respectively). Thus, it can be concluded that psychological counseling has a uniform impact in reducing the duration of playing games in these various age ranges.

Regarding visiting websites unrelated to learning, no significant interaction with age was observed, with p-values exceeding 0.05 for both the 35-44 versus 25-34 comparison (p-value 0.230) and the 45-54 versus 25-34 comparison (p-value 0.655). Therefore, the effect of online counseling on reducing digital distraction related to visiting irrelevant websites is uniform across all age groups; in other words, this effect is not dependent on age. Similarly, the reduction in distraction due to procrastination was also not influenced by age, as evidenced by p-values greater than 0.05 across all age groups. This shows that the online counseling model has proven to be effective for all age groups because the age factor does not have a significant influence on counselling outcomes. This is reinforced by the data in Table 5, where the 95% confidence interval for all age-related interactions showed consistent results, thus confirming that the effectiveness of the model remained stable and unchanged across different age groups.

Demographic factor analysis was also conducted, revealing the moderation of educational level as a factor influencing the effectiveness of online counseling. The results are presented in the following table:

Table 6: Moderation Analysis of Education Level on Digital Distraction Reduction

Predictor	**Estimate**	**SE**	**95% Confidence Interval**		**t**	**p**
			Lower	**Upper**		
Intercept[a]	92.794	6.126	71.0760	90.98	15.148	<.001
Education Level ✻ Hours spent on playing computer games:						
Bachelor’s/Diploma 4 – Master	0.561	1.146	-0.770	3.651	0.490	0.627
Diploma 1/2/3 – Master	-1.440	1.090	-2.884	1.762	-1.321	0.195
Education Level ✻ Visiting websites unrelated to learning:						
Bachelor’s/Diploma 4 – Master	-1.140	1.129	-1.110	3.329	-1.010	0.319
Diploma 1/2/3 – Master	1.112	1.093	-3.430	1.149	1.017	0.316
Education Level ✻ Distraction by procrastination:						
Bachelor’s/Diploma 4 – Master	-1.576	1.553	-2.260	4.19	-1.015	0.317
Diploma 1/2/3 – Master	0.964	1.590	-4.720	1.57	0.607	0.548

Note: SE = Standard Error; CI = Confidence Interval; t = t-statistic; p = p-value. p < 0.05 indicates statistical significance. [a]Intercept represents the baseline reference group (Master’s level). Interaction terms compare each education level category against the reference group.

Table 6 presents the results of a linear regression analysis that aims to test whether there is a difference in the influence between independent variables (such as duration of game play, visit to non-learning websites, and procrastination) on bound variables, based on the respondent's level of education. The main focus of this table is on the effect of interactions between education levels (with the reference group i.e. "Master") on specific activities. The Estimate column indicates the magnitude of the coefficient of influence, SE (Standard Error) indicates the degree of accuracy of the estimate, 95% Confidence Interval provides the lower and upper limits of the estimate, and the t and p values are used to determine statistical significance.

Based on these data, it can be concluded that none of the interaction variables had a statistically significant influence on the bound variables tested. This is indicated by the p-value of all predictors that is well above the standard significance threshold (usually 0.05). For example, in the “Bachelor's/Diploma 4 – Master” interaction related to hours played game, the p value was 0.627, which means that the difference in influence was not statistically significant. Similarly, for other predictors, where the Confidence Interval for each predictor included zero, which reinforced the finding that there was no significant difference in effects between these groups of education levels in the context of the activities studied.

These findings demonstrate that the effect of online counseling on reducing procrastination-related digital distraction is not attributable to educational level. Therefore, the effect of online counseling on reducing digital distraction is consistent across all educational level groups. Furthermore, the 95% confidence intervals for all educational level interactions, as detailed in Table 6, provide additional evidence for the stability of these findings across the different categories, confirming the lack of significant moderation in this professional cohort.

Discussion

The main findings of this study show that there is a very strong positive correlation between different types of digital distractions, such as gaming, social media use, and procrastination behavior. This indicates that digital distractions do not appear in isolation, but are a unit of interrelated behaviors (19). This phenomenon is in line with the concept of Problematic Internet Use (PIU), where a person who has difficulty managing himself in one digital activity tends to experience similar difficulties when interacting with other types of content or digital platforms (22).

A person's tendency to be distracted by digital devices is not a stand-alone problem, but a reflection of a more fundamental difficulty in terms of self-regulation (23). In practical terms, this implies that efforts to handle through counseling will not be effective if they are focused on only one type of digital disorder (24, 25). Because one form of disorder is often the trigger for another, a holistic approach is needed to address the root of the problem, rather than focusing only on the specific symptoms that appear on the surface.

Although all the factors (dimensions) studied are closely interrelated, each factor has a different degree of influence in determining the success of an intervention. Procrastination was identified as the most dominant factor in predicting success, suggesting that the success of such interventions is highly dependent on improving one's self-regulation and time management skills (26). In addition, the duration of gaming is also a significant predictor factor, indicating that structured digital behavior is easier to change or regulate through cognitive-behavioral techniques in counseling than other forms of disorder that are more abstract in nature, such as social media use (27).

Regression analysis showed that procrastination was the strongest predictor of a decline in post-psychological counseling digital disorders, which confirms previous findings that time management failures are a major factor in difficulty maintaining focus during online learning (28). Therefore, handling procrastination is a crucial step to reduce the overall number of digital disruptions (29). In addition, the habit of accessing non-academic sites and playing online games has also been shown to be a significant predictor of distraction reduction, where online psychological counseling has been shown to be effective as an intervention to modify such unproductive digital behaviors (30).

Digital games (video games) have a much more structured and clearer pattern of behavior when compared to other activities on the internet, such as surfing social media or watching videos. The rigid structure of the game which consists of systematic elements such as rewards, levelling up, and measurable challenges makes player behavior easier to predict and map. Because of its structured nature, experts argue that behaviors that arise from gaming can be more easily intervened or changed through psychological methods, especially cognitive-behavioral interventions. In contrast, the algorithms that run social media are highly abstract, dynamic, and have no clear boundaries, making them much more difficult to manage or modify their behavior through the same clinical approach (31).

This research contributes to counselors in identifying and addressing specific gaming behaviors that cause concentration disorders (32). While these findings suggest that some certain digital behaviors are easier to change than others, more research is needed to confirm this, in line with past theories (31, 33). However, the study found that other digital activities such as social media use, watching entertainment videos, unwanted content, and digital addiction did not show a significant correlation with reduced distractions after brief counseling. This is likely to happen because the behavior is driven by complex motivations (such as social, emotional, and informational needs) that are difficult to address in limited counseling sessions, as well as the presence of other external factors such as addiction levels, social support, or individual mental health conditions that affect the success of the intervention (34).

Comprehensive strategies that need to be implemented in counseling to help online learners (especially on MOOC platforms) overcome digital disruption (35, 36). Overcoming complex digital distractions in the world of education requires an integrative approach that harmoniously combines psychological, technical, and social aspects. Psychologically, individuals are helped to identify and change procrastination mindsets through the Cognitive Behavioral Therapy (CBT) method as well as train metacognitive awareness through urge surfing techniques to manage digital impulses (37, 38). This step is reinforced by technical interventions, such as the use of website blockers that serve as external structures to support self-discipline (39, 40), as well as supported by the social dimension through a study-buddy system that effectively reduces feelings of isolation (41). By integrating these three aspects, educational institutions can create a learning ecosystem that is more structured, effective, and able to minimize the influence of digital disruption as a whole (3, 42).

The effectiveness of online counseling in overcoming digital distractions is universal and does not depend on a person's demographic background, such as gender, age, or education level (7). This indicates that online counseling is an inclusive solution that can be widely applied to anyone. However, the results of this study are still preliminary due to the limited number of samples, so the interpretation needs to be done carefully. In essence, the success of this method is determined more by the quality of the program structure and the ease of access to services than by the personal characteristics of the participants, which strengthens the position of online counseling as an approach that is applicable to various levels of society (43).

This research makes an important contribution to mapping the phenomenon of digital disruption that is often experienced by learners when participating in Massive Open Online Courses (MOOCs), where the problem proves to be complex because it is triggered by psychological factors and individual behavior. As a solution, the study confirms that counseling interventions focused on dealing with procrastination, access to irrelevant websites, and gaming addiction have been shown to be effective in minimizing these disorders. By applying a psychological approach that is precisely targeted, learners are expected to be able to control behaviors that hinder concentration so that the learning process can take place with a more stable and maintained focus.

The results of this study cannot be generalized or applied widely to the general public because the subjects of the research have very specific characteristics, namely the State Civil Apparatus (ASN) in Central Java. The differences in the backgrounds of ASNs, such as work motivation, career development demands, and discipline driven by professional obligations, create a unique pattern of interaction when using online learning programs (MOOCs). This is what causes their learning behavior not to be equated with ordinary students or other general participants. Therefore, the author warns us to be careful in concluding that the methods or results of successful interventions in this ASN group will have exactly the same impact if applied to other more diverse educational groups or cultures.

Conclusion

The essence of the study's findings is that although various forms of digital distraction are interrelated, not all of them have the same effect on the effectiveness of counseling. The study identified that procrastination was the most significant determinant in efforts to reduce digital distractions, followed by the duration of gaming and visiting irrelevant websites, while other factors such as social media use did not appear to have a statistically significant impact. Therefore, this study suggests that future interventions should be more focused on handling procrastination and gaming habits, and emphasize the importance of improving psychological aspects such as time management and self-regulation to improve the quality of the learning experience of MOOC participants.

Limitations

Specifically, the author acknowledges that the small number of participants (only 43 people) and the limited background of respondents, namely only civil servants (ASN) in Central Java, make the findings of this study difficult to generalize or be applied widely to the more diverse population of Massive Open Online Courses (MOOC) users. Although the research instrument is declared valid and reliable, the authors suggest that future research use a larger, varied sample and come from different professional backgrounds to reduce bias and increase the statistical power of the research. Finally, despite all its shortcomings, this research remains considered an important foundation that makes a real contribution to understanding the phenomenon of digital disruption in online learning, which can help design more effective interventions for future learners.

Abbreviations

AI: Artificial Intelligence, ASN: Aparatur Sipil Negara (Civil Servant), IQR: Interquartile Rank, MOOC: Massive Open Online Course, PIU: Problematic Internet Use.

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Author Contributions

Titi Prihatin: Conceptualization, Research Design, Ghanis Putra Widhanarto: Formal analysis, Data interpretation, Writing – Original Draft, Dwi Yuwono Puji Sugiharto: Methodology, Supervision, Arif Rachman: Investigation, Validation, Seftia Kusumawardani: Writing – Review and Editing, Literature review.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance Process

The authors declare that generative artificial intelligence (AI) and AI-assisted technologies were used for language refinement and grammatical improvement during the preparation of this manuscript. The authors take full responsibility for the content, originality, accuracy, and integrity of the work.

Ethics Approval

This study was conducted in accordance with ethical standards for research involving human participants. Informed consent was obtained from all participants prior to data collection. Ethical approval was obtained from the relevant institutional review board.

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