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Jurnal Ilmiah Ilmu Terapan Universitas Jambi
Vol. 10 No. 2. April 2026, pp. 859-870 DOI. 10.22437/jiituj.v10i2.53029

Research Article

REGULATION AND DIGITAL DISTURBANCE IN ACADEMIC PROCRASTINATION: EVIDENCE FROM A GENDER-INVARIANT STRUCTURAL MODEL

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Article Info
Recieved: Jan 12, 2026
Revised: Feb 26, 2026
Accepted: Mar 29, 2026
OnlineVersion: Apr 29, 2026

Abstract
Academic procrastination remains prevalent in higher education, and digitally saturated learning environments may amplify students' task delays. This study aims to test an integrative structural model linking self-regulation and digital disturbance to academic procrastination and to examine whether the measurement model operates equivalently across gender. Using a quantitative ex post facto design, data were collected from 216 Indonesian undergraduate students via validated 5-point Likert instruments measuring self-regulation, digital disturbance, and academic procrastination. Structural Equation Modeling with maximum likelihood estimation was conducted, followed by multi-group confirmatory factor analysis to assess gender measurement invariance. Results showed that self-regulation negatively predicted academic procrastination ($\beta = -0.290$, $p < .001$), while digital disturbance positively predicted academic procrastination ($\beta = 0.544$, $p < .001$); self-regulation was also negatively associated with digital disturbance ($\beta = -0.268$, $p = .002$). The model explained 46.5% of the variance in academic procrastination ($R^2 = 0.465$). Measurement invariance testing supported equivalence up to the scalar level across gender, enabling unbiased cross-gender interpretation of the constructs. The novelty of this study lies in combining a digitally relevant predictor (digital disturbance) with gender-invariant measurement validation within a single SEM framework in an Indonesian undergraduate context. Practically, the findings imply that universities should strengthen students' self-regulated learning while managing digital interruptions through attention-management training and instructional policies to reduce procrastination.

Keywords: Academic Procrastination, Digital Disturbance, Gender-Invariant Structural Model, Self-Regulation

INTRODUCTION

Academic demands in higher education should ideally contribute to shaping students' character, fostering independence, responsibility, and the capacity to manage the complexities of their studies. To support these outcomes, institutions also provide a range of academic resources to help students meet established standards of academic quality (Bakker & Mostert, 2024). However, when academic demands are not balanced by adaptive learning experiences, students may exhibit dysfunctional behaviors such as academic procrastination, study dissatisfaction, and intentions to drop out (Ragusa et al., 2023; Scheunemann et al., 2022). These behaviors not only contribute to delayed graduation and declining academic achievement, but also generate adverse institutional consequences, including reputational harm, financial losses due to reduced tuition revenue, and diminished potential for alumni contributions in the future (Scheunemann et al., 2022; Zacks & Hen, 2018).

Academic procrastination is commonly understood as a prevalent and maladaptive failure of self-regulation, yet it has not been fully elucidated in a comprehensive manner (Chun Chu & Choi, 2005). Reviews of conceptual, theoretical, and empirical studies drawing on correlational, experimental, and qualitative evidence indicate that personality traits such as neuroticism, rebelliousness, and sensation seeking are only weakly associated with procrastination. In contrast, strong and consistent predictors include task aversiveness, low self-efficacy, impulsivity, and self-regulatory components of conscientiousness such as self-control, distractibility, organization, and achievement motivation (Ragusa et al., 2023; Yuan et al., 2024). This pattern aligns with Temporal Motivation Theory, which integrates expectancy theory and hyperbolic discounting, and underscores the need for further research given the high prevalence of procrastination and its wide-ranging consequences in higher education contexts. Self-regulated performance plays a central role in voluntarily regulating academic activities, including thoughts, emotions, and behaviors, to achieve goals such as learning and completing assignments(Li & Zheng, 2018; Lourenço et al., 2025; Zimmerman & Moylan, 2009).

When this capacity does not function optimally, procrastination may emerge, defined as the tendency to delay or avoid tasks that are, in fact, under an individual's control (Li & Zheng, 2018). Students with weak self-regulation often experience difficulties in time management and in controlling their learning behaviors (Ateş Akdeniz, 2023; Shamla & Jayan, 2025). This condition is common among university students and undermines learning effectiveness, highlighting the need for instructional strategies and interventions that strengthen self-regulation (Ragusa et al., 2023; Zimmerman & Moylan, 2009). Accordingly, assessing students' propensity to procrastinate is important as a foundation for developing more targeted academic and motivational interventions (Tuckman, 1991). Evidence regarding gender differences in procrastination adds nuance, even though observed differences in higher education tend to be small (Alqahtani & Al-Momen, 2025). Although empirical findings often show no significant differences between men and women in the incidence or frequency of academic procrastination, gender role orientation plays an important role in explaining the underlying reasons or motives for delaying tasks {Citation}). In this study, we therefore support conducting gender measurement invariance testing to determine whether the developed instrument functions equivalently across gender subgroups (male and female) (Shaw & Zhang, 2021).

In parallel, the misuse of digital devices in students' daily lives has been shown to be closely associated with academic dysfunction, negatively affecting key psychological dimensions and increasing anxiety (Fang & White, 2025; Herut & Gorfu, 2024). Empirical evidence also indicates that digital literacy is negatively correlated with academic delay (Jamil et al., 2025; Savaş et al., 2025). This claim is supported by a study of 532 smartphone-using students at Johannes Gutenberg University Mainz, Germany, where technology-related addictive behaviors, such as prolonged phone-checking, were found to explain variability in procrastination at small-to-moderate levels (Meier, 2022). More concerningly, digital disturbances experienced by students have been linked to poor sleep quality and mental health problems via heightened anxiety and stress(Uppal & Hajian, 2024). In this study, digital disturbance refers to recurrent technology-driven interruptions (e.g., notifications, habitual checking, and attention shifts) that disrupt students'sustained academic engagement.

Although research on academic procrastination has advanced by identifying a range of psychological and contextual predictors, most studies still focus on testing associations among variables without establishing whether the constructs are measured equivalently across different student groups, particularly by gender. Yet differences in academic experiences, self-regulation patterns, and responses to digital distractions between male and female students have been widely reported, potentially influencing how respondents interpret and respond to questionnaire items. Without testing measurement invariance, interpretations of differences or similarities in procrastination scores risk being biased because they may reflect differences in how the instrument is understood rather than true differences in the underlying construct (Martin et al., 2025). Therefore, beyond examining the structural relations among self-regulation, digital disturbance, and academic procrastination, it is essential to ensure that the questionnaire instrument operates consistently and fairly across genders. Addressing this need, the present study integrates gender measurement invariance testing as a key step in validating the measurement model, enabling the relationships among constructs to be interpreted more accurately and with reduced risk of measurement bias.

Accordingly, this study aims to (1) validate the measurement model of self-regulation, digital disturbance, and academic procrastination, (2) test the structural effects of self-regulation and digital disturbance on academic procrastination using Structural Equation Modeling, and (3) evaluate gender-based measurement invariance (configural, metric, and scalar) prior to cross-gender interpretation. The novelty of this study lies in integrating a digitally relevant predictor (digital disturbance) with gender-invariant measurement validation within a single SEM framework in an Indonesian undergraduate context, thereby enabling more defensible substantive conclusions and practical recommendations. The next section describes the research design, participants, instruments, and data analysis procedures.

RESEARCH METHOD

Research Design

This study employed a quantitative approach with an ex post facto design to examine the structural relationships among three latent constructs: Self-Regulation (SR), Digital Disturbance (DD), and Academic Procrastination (AP). Structural Equation Modeling (SEM) was used to test the hypothesized model and estimate the magnitude of relationships among constructs. In addition, multi-group analysis was conducted to evaluate measurement invariance (MI) across gender, ensuring that the measurement model functioned equivalently for male and female students.

Research Target/Subject

The target population comprised undergraduate students in Indonesia. A total of 216 students participated in the study. Participants were recruited using purposive sampling with the following inclusion criteria: (1) currently enrolled as undergraduate students, (2) having completed at least four semesters of study, and (3) having experience using digital media in everyday academic activities.

Research Procedure

First, the study developed a hypothesized model linking SR and DD to AP. Second, the questionnaire was administered to eligible participants after they met the inclusion criteria. Third, the collected data were screened for completeness and suitability for SEM analysis. Fourth, the measurement model was evaluated through confirmatory factor analysis (CFA) prior to testing the structural model. Finally, measurement invariance across gender was tested hierarchically to confirm equivalence of the measurement model before interpreting group comparisons.

Instruments, and Data Collection Techniques

Data were collected using a closed-ended questionnaire administered to undergraduate students. All items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument comprised three sections corresponding to the study constructs: (1) Self-Regulation, (2) Digital Disturbance, and (3) Academic Procrastination. The questionnaire was designed to capture students' self-reported regulation of learning behavior, experiences of digital distraction during academic activities, and tendencies to delay academic tasks.

Table 1. Construct Self Regulation and Digital Disturbance

Construct	Dimension	Item Code	Item Statement
Self-Regulation	Time Management	S1	I feel that I can complete assignments within the time I set to finish them.
	Time Management	S2	I have a clear schedule for completing my academic tasks.
	Self-Control	S3	I can resist the urge to do more enjoyable activities (e.g., playing or relaxing) in order to complete academic assignments.

Construct	Dimension	Item Code	Item Statement
	Self-Control	S4	I feel that I can control myself to work on assignments even when I do not feel like doing so.
	Self-Control	S5	I am able to keep working on assignments even when I feel tired or unmotivated.
Digital Disturbance	Frequency of Disruption	G1	I often check social media repeatedly throughout the day even when it is not needed for academic purposes.
	Task-Related Distraction	G2	When I use social media, I find it difficult to refocus on academic tasks after my attention has been diverted.
	Task-Related Distraction	G3	Using social media makes me delay completing academic assignments.
	Attention/Self-Control During Study	G4	I find it difficult to control myself from opening social media while working on academic assignments.
	Attention/Self-Control During Study	G5	I often feel that social media distracts me from important academic work.
	Academic Performance Impact	G6	I often postpone academic work because I am more interested in browsing social media.
	Academic Performance Impact	G7	Social media reduces my motivation to complete academic assignments on time.

Table 2. Academic Procrastination Instrument Grid (Tuckman Procrastination Scale Adaptation)

Construct	Dimension	Item Code	Item Statement	Keying
Academic Procrastination	Task delay (important tasks)	P1	I delay completing important work even though I know it should be finished soon.	+
	Task initiation delay (disliked tasks)	P2	I delay starting tasks that I do not like.	+
	Deadline delay (last-minute work)	P3	When there is a deadline for a task, I usually wait until the last moment to complete it.	+
	Decisional procrastination	P4	I delay making difficult decisions.	+
	Study-habit improvement delay	P5	I put off efforts to improve my study habits.	+
	Avoidance rationalization	P6	I often look for excuses not to do something.	+
	Planning/effort allocation (boring tasks)	P7	I allocate the necessary time to complete boring tasks such as studying.	Reverse (R)
	Time waste / difficulty changing habits	P8	I often feel that my time is wasted and it is difficult to change this habit.	+
	Avoidance under difficulty	P9	When I face something too difficult, I believe it is better to postpone it.	+
	Follow-through delay (commitments)	P10	When I promise to do something, I often delay doing it.	+
	Plan adherence	P11	When I make an action plan, I usually follow that plan.	Reverse (R)
	Negative affect without action	P12	If I fail to finish a task, I dislike myself, but that feeling does not motivate me to act.	+

Construct	Dimension	Item Code	Item Statement	Keying
	Starting inhibition	P13	I feel stuck and unable to start something even though I know it is important to begin.	+
	No next-day delay	P14	I never postpone work until the next day; I usually finish today's tasks today.	Reverse (R)

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Data analysis technique

Data were analyzed using Structural Equation Modeling (SEM) with maximum likelihood estimation. Prior to model estimation, the dataset was screened for missing values, outliers, and distributional assumptions to ensure suitability for ML-based SEM. The analysis proceeded in sequential stages. 1) a confirmatory factor analysis (CFA) was conducted to evaluate the measurement model of each construct (SR, DD, and AP). Measurement quality was assessed using standardized factor loadings, composite reliability (CR), and average variance extracted (AVE). Model fit was evaluated using multiple indices, namely CFI, TLI, RMSEA, and SRMR. 2) the structural model was tested to estimate standardized path coefficients among SR, DD, and AP, and the explained variance of academic procrastination (R^2). Statistical significance of standardized estimates was evaluated using z-values and p-values. 3) gender-based measurement invariance was examined using multi-group CFA in a hierarchical sequence: configural invariance (same factor structure), metric invariance (equal factor loadings), scalar invariance (equal loadings and intercepts), and strict invariance (equal residual variances). Invariance decisions were guided primarily by changes in incremental fit indices (e.g., ΔCFI) in conjunction with chi-square difference tests. All results were reported in terms of model-fit statistics, standardized estimates (β), and variance explained (R^2), consistent with the analytical stages described above.

RESULTS AND DISCUSSION

This study aimed to describe the construct structure of the self-regulation (SR), digital disturbance (DD), and academic procrastination (AP) instruments using Structural Equation Modeling (SEM), and to examine measurement equivalence across groups (gender) through Measurement Invariance (MI) analysis. The structural model comprised three latent constructs: SR, DD, and AP. Model estimation was conducted using Maximum Likelihood (ML) with data from 216 undergraduate students (male and female) across multiple study programs. This sample size was considered adequate for SEM, consistent with the recommendation by (Hair et al., 2019) that the minimum sample size should be 5–10 times the number of indicators in the measurement model.

The measurement model comprising three latent constructs (self-regulation [SR], digital disturbance [DD], and academic procrastination [AP]) was evaluated using confirmatory factor analysis (CFA). The overall model demonstrated acceptable fit to the data: CFI = 0.852, TLI = 0.837, RMSEA = 0.069 (90% CI: 0.061–0.077), and SRMR = 0.082. All retained indicators loaded significantly on their intended constructs ($p < 0.001$), with standardized loadings above 0.50. AP was measured by 14 indicators (P1–P14) with loadings ranging from 0.509 to 1.00; SR was measured by five indicators (S1–S5) with loadings ranging from 0.57 to 0.79; and DD was measured by seven indicators (G1–G7) with loadings ranging from 0.63 to 0.81 (Figure 1). Indicator R^2 values ranged from 0.000 to 0.491 for AP, 0.330 to 0.627 for SR, and 0.393 to 0.654 for DD. Internal consistency was adequate based on composite reliability (AP = 0.778; SR = 0.820; DD = 0.888). Convergent validity (AVE) was 0.288 for AP, 0.492 for SR, and 0.531 for DD. Discriminant validity was supported by HTMT values below common cutoffs (AP–SR = 0.388; AP–DD = 0.627; SR–DD = 0.177), indicating that the three constructs were empirically distinct.

The structural model tested the effects of self-regulation and digital disturbance on academic procrastination. The model explained 46.5% of the variance in academic procrastination ($R^2 = 0.465$). Self-regulation negatively predicted academic procrastination (SR → AP: $\beta = -0.290$, $z = -3.757$, $p < 0.001$). Digital disturbance positively predicted academic procrastination (DD → AP: $\beta = 0.544$, $z = 5.559$, $p < 0.001$). In addition, self-regulation was negatively associated with digital disturbance (SR ↔ DD: $\beta = -0.268$, $z = -3.081$, $p = 0.002$). Table 3 summarizes the standardized path estimates.

Table 3. Structural Equation Model

Path	(β; Std.all)	p	Direction & significance
SR → AP	-0.290	< 0.001	Negative, significant
DD → AP	0.544	< 0.001	Positive, significant
SR ↔ DD	-0.268	0.002	Negative covariance, significant

Next, the indicator R^2 values were examined to assess the proportion of item variance explained by each latent construct. For Academic Procrastination, item R^2 values ranged from 0.000 to 0.491 (e.g., P10 = 0.491; P5 = 0.469; P2 = 0.431). However, several indicators showed very low R^2 values, namely P11 = 0.000, P14 = 0.048, and P7 = 0.099, indicating that these items were weakly explained by the Academic Procrastination construct in the current model. For Self-Regulation, indicator R^2 values ranged from 0.330 to 0.627 (S3 = 0.627; S2 = 0.575; S1 = 0.443), whereas for Digital Disturbance they ranged from 0.393 to 0.654 (G5 = 0.654; G4 = 0.632; G6 = 0.579). At the structural level, the R^2 for Academic Procrastination was 0.465, indicating that approximately 46.5% of the variance in Academic Procrastination was explained by the model predictors (Self-Regulation and Digital Disturbance). Notably, this pattern does not support the earlier statement that R^2 values ranged from 0.21 to 0.90; the observed range in the reported output was 0.000–0.654 for indicators, and 0.465 for the Academic Procrastination latent construct.

Structural path estimates showed that self-regulation negatively predicted academic procrastination ($\beta = -0.290$, $z = -3.757$, $p < 0.001$), whereas digital disturbance positively predicted academic procrastination ($\beta = 0.544$, $z = 5.559$, $p < 0.001$). In addition, self-regulation was negatively associated with digital disturbance ($\beta = -0.268$, $z = -3.081$, $p = 0.002$). Overall, the model explained 46.5% of the variance in academic procrastination ($R^2 = 0.465$). Self-regulation had a significant negative effect on academic procrastination ($\beta = -0.290$, $p < 0.001$), indicating that higher levels of students' self-regulatory capacity are associated with a lower tendency to delay academic tasks. In contrast, digital disturbance had a significant positive effect on academic procrastination ($\beta = 0.544$, $p < 0.001$), suggesting that greater exposure to digital disruptions (e.g., social media notifications and excessive device use) is linked to a stronger tendency to postpone coursework. In addition, self-regulation was negatively associated with digital disturbance ($\beta = -0.268$, $p = 0.002$), indicating that students with stronger self-regulation tend to exert better control over digital device use and minimize distractions during learning. The explained variance for academic procrastination was $R^2 = 0.465$, meaning that 46.5% of the variance in students' academic procrastination can be accounted for by the two main predictors, self-regulation and digital disturbance, while the remaining 53.5% is attributable to factors outside the model

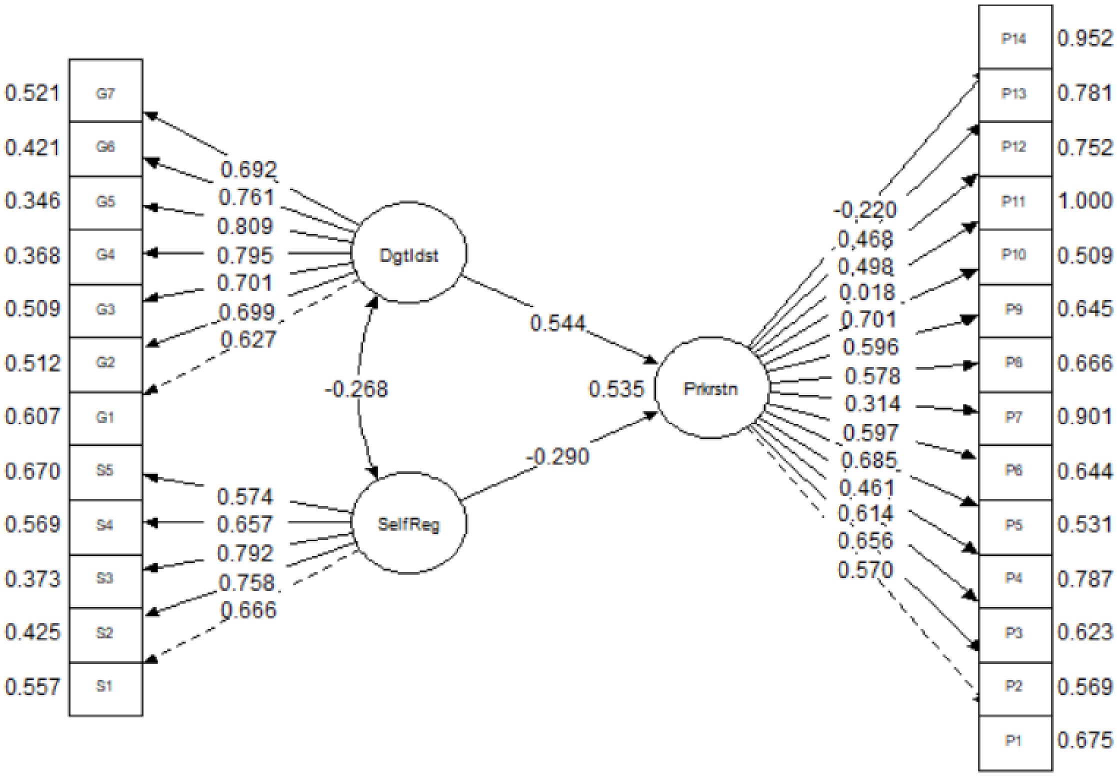

Figure 1. SEM

Measurement invariance across gender was evaluated hierarchically for the SR, DD, and AP measurement model using multi-group CFA (configural, metric, scalar, and strict). The configural model showed acceptable baseline fit (CFI = 0.802, TLI = 0.783, RMSEA = 0.083), supporting a comparable factor structure across male and female students. Constraining factor loadings (metric invariance) yielded CFI = 0.789, TLI = 0.777, RMSEA = 0.084, with $\Delta\chi^2(23) = 52.579$, p = 0.0004 and ΔCFI = 0.013. Constraining loadings and intercepts (scalar invariance) produced CFI = 0.782, TLI = 0.778, RMSEA = 0.084, with $\Delta\chi^2(23) = 37.393$, p = 0.0296 and ΔCFI = 0.007. Adding equality constraints on residual variances (strict invariance) resulted in CFI = 0.770, TLI = 0.775, RMSEA = 0.084, with $\Delta\chi^2(26) = 53.970$, p = 0.0010 and ΔCFI = 0.012. Table 4 presents the invariance testing results.

Table 4. Hierarchical Measurement Invariance Testing Across Gender (Configural, Metric, Scalar, Strict)

Procedur	CFI	TLI	RMSEA	$\Delta\chi^2$(df)	p	ΔCFI
Configural	0.802	0.783	0.083	–	–	–
Metric	0.789	0.777	0.084	52.579 (23)	0.0004	0.013
Scalar	0.782	0.778	0.084	37.393 (23)	0.0296	0.007
Strict	0.770	0.775	0.084	53.970 (26)	0.0010	0.012

This study aimed to test a structural model of academic procrastination by examining the roles of self-regulation and digital disturbance among undergraduate students. In addition, the study sought to establish gender-based measurement equivalence for the instruments used, so that model interpretations could be made fairly and without bias between male and female students. The findings provide empirical evidence that academic procrastination in university students is a multifactorial phenomenon shaped simultaneously by internal factors such as self-regulation (Alqahtani & Al-Momen, 2025; Ragusa et al., 2023; Zimmerman & Moylan, 2009) and external factors such as digital disturbance (Meier, 2022). The proposed structural model indicates that these two constructs explain nearly half of the variance in academic procrastination, underscoring the value of an integrative approach to understanding task delay in higher education (Zacks & Hen, 2018). These results position procrastination not merely as an individual habit problem, but as an outcome of the interaction between self-management capacity and the demands of a digitally mediated learning environment. This integrative framing is consistent with recent synthesis work that conceptualizes digital distraction as a technology person environment phenomenon that can disrupt learning through sustained attentional interference (Martin et al., 2025).

The significant negative effect of self-regulation on academic procrastination reinforces the self-regulated learning framework, which conceptualizes self-regulation as a core mechanism underlying academic success. Students who are able to plan, monitor, and evaluate their learning behaviors are more likely to initiate and complete academic tasks on time. This finding is consistent with (Zimmerman & Moylan, 2009) who argue that failures in self-regulation constitute a primary basis of procrastination, and it also aligns with temporal motivation theory, which conceptualizes procrastination as a failure to manage task expectancy and value over time (Gao et al., 2025; Svartdal & Løkke, 2022). Furthermore, these findings reinforce the view that self-regulation functions as a protective factor against a range of academic dysfunctions. Students with strong self-regulation are not only more organized in managing their time, but also possess the metacognitive and motivational capacity to cope with the discomfort often associated with academic tasks. This interpretation is consistent with Ragusa et al., (2023) who reported that strengthening self-regulation contributes to lower academic stress, anxiety, and procrastination, while enhancing students' learning resilience. In line with existing empirical evidence, conscientiousness has also been shown to have a robust negative association with student procrastination. Higher levels of orderliness, responsibility, discipline, and goal orientation are closely aligned with stronger self-regulatory capacity (Ateş Akdeniz, 2023; Li & Zheng, 2018; Ye et al., 2025).

Digital disturbance, in essence, represents cognitive and behavioral disruption arising from interruptions generated by digital technologies, such as notifications and the impulse to check one's device, which divert attention from primary tasks. Such disruptions can undermine self-regulation, reduce sustained focus, and ultimately increase the likelihood of delaying academic task completion. The strong positive effect of digital disturbance on academic procrastination underscores digital distraction as a central challenge in contemporary learning contexts. Smartphone notifications, social media engagement, and repeated mobile checking have been shown to fragment attention and prolong task delay. This finding is consistent with (Yuan et al., 2024), who emphasize that the core issue is not merely the intensity of technology use, but students' difficulty in regulating attention within highly distracting digital environments. Notably, evidence from Meier (2022) indicates that mobile checking habit strength and perceived interruptions are meaningfully associated with procrastination and reduced well-being, supporting the interpretation that "interruptive checking" is a relevant proximal mechanism. In addition, a recent meta-analysis reported a significant positive relationship between smartphone addiction and procrastination across studies, suggesting that technology-related dysregulation is a stable correlate of procrastination in student populations (Chen & Lyu, 2024).

Beyond its direct impact on procrastination, digital disturbance is also associated with broader psychological consequences, including mental fatigue, poor sleep quality, and heightened anxiety. Studies by (Mojibpour et al., 2025; Uppal & Hajian, 2024) suggest that technology dependence can contribute to a reinforcing cycle of academic dysfunction and deteriorating mental health among university students. Accordingly, academic procrastination in digital contexts should be understood as part of students' learning well-being rather than being treated solely as a time-management problem. This perspective highlights the strategic role of higher education institutions in designing preventive interventions through digital literacy policies, strengthening students' self-regulation, and developing instructional designs that are adaptive to digital learning environments (Georgopoulou et al., 2025; Jartitngarm, 2025). Complementary synthesis evidence also links problematic smartphone use to poorer academic outcomes, reinforcing the practical relevance of addressing digital-related risk factors in academic settings (Paterna et al., 2024).

The negative association between self-regulation and digital disturbance further indicates that students with stronger self-regulatory capacity are better able to manage digital device use during learning activities. This finding implies that self-regulation functions as a mechanism for controlling digital distractions, thereby reducing the adverse effects of technology-rich environments on academic behaviors. The result is consistent with (Savaş et al., 2025; Yuan et al., 2024), who highlight digital literacy and self-control as key factors in minimizing digital burnout and procrastination. From an applied perspective, this pattern suggests that interventions should not only target procrastination outcomes, but also strengthen the self-regulatory "control system" that helps students resist impulsive checking and recover attention after interruptions. However, intervention evidence on notifications suggests that disabling notifications alone may not be sufficient for behavior change; attention-management strategies and habit-level supports may be needed to reduce checking and procrastination more reliably (Dekker et al., 2025).

Practically, these findings suggest that interventions to reduce academic procrastination do not need to be differentiated by gender; instead, they should prioritize strengthening self-regulation and managing digital distractions. Programs that foster self-regulated learning, attention-management training, and campus policies governing technology use in learning environments may represent effective strategies. This approach aligns with the recommendations of (Zacks & Hen, 2018) who emphasize interventions targeting self-regulatory skills as a sustainable, long-term solution. Concretely, universities can (a) integrate self-regulated learning micro-skills (goal setting, implementation intentions, time blocking, self-monitoring) into first-year seminars, and (b) implement “digital interruption hygiene” supports (notification education, structured focus intervals, device norms during high-demand academic tasks). Given evidence that digital distraction in education is shaped by technology, personal habits, and environmental design, interventions are likely to be most effective when they address all three layers rather than focusing on device restrictions alone (Martin et al., 2025).

Overall, this study contributes to the literature by integrating a structural model of academic procrastination with cross-gender measurement validation within a comprehensive analytical framework. The novelty lies in combining a digitally salient contextual predictor (digital disturbance) with explicit gender-based measurement invariance evaluation in one SEM model within an Indonesian undergraduate context, strengthening both substantive and methodological defensibility.

Nevertheless, limitations such as the cross-sectional design and reliance on self-reported data should be acknowledged. First, the cross-sectional design limits causal interpretation; longitudinal work is needed to test temporal ordering (e.g., whether digital disturbance precedes increases in procrastination or whether procrastination increases device checking). Second, self-report measures may inflate associations due to common-method variance and recall bias; future studies should triangulate self-reports with behavioral indicators (e.g., screen-time logs, notification exposure, learning analytics, or experience sampling). Third, the convergent validity for academic procrastination was relatively weak (low AVE), which suggests the need for instrument refinement by revising or removing weak indicators and re-testing the measurement model in independent samples. Fourth, subgroup sample sizes can reduce sensitivity in multi-group testing at stricter invariance levels; replication with larger and more balanced gender group sizes is recommended. Future research is encouraged to test this model longitudinally and to examine additional factors, including institutional context and pedagogical strategies, to further elucidate the dynamics of academic procrastination in the digital era. Intervention research that combines self-regulation training with digital interruption management may be particularly valuable, especially given evidence that single-component approaches (e.g., notification disabling) may yield limited effects (Dekker et al., 2025).

CONCLUSION

This study demonstrates that academic procrastination among undergraduate students is jointly shaped by self-regulation and digital disturbance. Self-regulation is negatively associated with academic procrastination, whereas digital disturbance is positively associated with academic procrastination, and the model explains a substantial proportion of variance in procrastination ($R^2 = 0.465$). Evidence of gender-based measurement invariance up to the scalar level supports fair interpretation of the constructs across male and female students. Practically, higher education institutions should prioritize interventions that strengthen students’ self-regulated learning skills and reduce technology-driven interruptions through digital literacy and attention-management supports embedded in instructional design. Future research should replicate these findings using longitudinal or experimental designs and refine the procrastination measurement to strengthen convergent validity.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the support provided by the Rector of Universitas Islam Nahdlatul Ulama Jepara and the Rector of Universitas Wahid Hasyim Semarang, as well as the Institute for Research and Community Service (LPPM), Universitas Islam Nahdlatul Ulama Jepara, and the Institute for Research, Development, and Community Engagement (LP3M), Universitas Wahid Hasyim Semarang. The authors also extend their sincere appreciation to the collaborative team of faculty members from Universitas Islam Nahdlatul Ulama Jepara (UNISNU) and Universitas Wahid Hasyim Semarang (UNWAHAS) for their valuable cooperation, academic input, and contributions throughout the study.

AUTHOR CONTRIBUTIONS

Conceptualization, Linda Indiyarti Putri and Ahmad Saefudin; Methodology, Linda Indiyarti Putri and Nusrotus Sa'idah.; Software, Nusrotus Sa'idah.; Validation, Asmaul Husna, Aris Abdul Ghoni, Yushinta Eka Farida.; Formal Analysis, Linda Indiyarti Putri and Nusrotus Sa'idah; Investigation, Linda Indiyarti Putri and Yushinta Eka Farida.; Resources, Asmaul Husna, Aris and Abdul Ghoni.; Data Curation, Linda Indiyarti Putri and Ahmad Saefudin; Writing – Original Draft Preparation, Linda Indiyarti Putri and Nusrotus Sa'idah; Writing – Review & Editing, Linda Indiyarti Putri and Ahmad Saefudin; Visualization Linda Indiyarti Putri and aris Abdul Ghoni; Supervision, Nusrotus Sa'idah and Asmaul Husn.; Project Administration, Linda Indiyarti Putri and Nusrotus Sa'idah; Funding Acquisition, Linda Indiyarti Putri and Nusrotus Sa'idah All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest. The supporting institutions had no role in the study design; data collection, analysis, or interpretation; manuscript preparation; or the decision to publish the results.

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