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Fostering Personal Growth Through Self-Regulation: The Roles of Cognitive, Affective, and Motivational Feedback

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Abstract

Feedback plays a fundamental role in supporting students' learning and personal development, yet previous studies have largely examined cognitive and affective feedback separately, providing limited understanding of how they jointly promote personal growth through self-regulation. This study investigated the relationships among cognitive feedback, affective feedback, motivation, self-regulation, and personal growth and understanding in higher education. A quantitative cross-sectional design was employed involving 450 university students, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings demonstrate that cognitive feedback, affective feedback, and learning motivation each make meaningful contributions to strengthening students' self-regulation. In turn, self-regulation emerged as a key predictor of personal growth and deeper understanding while also serving as the mechanism through which feedback and motivation influence these outcomes. These findings underscore the importance of integrating cognitive and affective feedback practices to cultivate students' motivation, strengthen self-regulated learning, and support holistic personal development. The study contributes an integrated feedback framework that highlights self-regulation as a central process linking instructional feedback to meaningful learning and personal growth in higher education.

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INTRODUCTION

Feedback plays a vital role in shaping the learning experience, influencing students' motivation, engagement, and overall academic development. However, in current school life practices, the implementation of feedback from teachers to students still faces various challenges. Many teachers tend to provide feedback that is general, late, or only focuses on final grades without including explanations that help students understand their learning process (Ding, 2025). This can hinder students' ability to reflect on their progress and limit the development of independent learning skills. In addition, affective feedback such as praise, emotional encouragement, or empathetic responses is still rarely provided consistently, especially in school environments that only reflect cognitive achievement (Brandmo & Gamlem, 2025). As a result, students often feel a lack of emotional support, which has an impact on decreasing their motivation and personal development. Furthermore, only a small portion of feedback meets the criteria of being specific, timely, and constructive, which are essential for improving students' self-efficacy in the learning process (Wang et al., 2023). This inadequate use of feedback not only affects students' immediate

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learning responses but also hinders their broader personal growth and understanding, such as self-awareness, reflective thinking, and emotional resilience, three key pillars in holistic educational outcomes (Mahmoudi et al., 2012).

Recent research indicates that cognitive feedback, which provides structured, performance-related insights, is essential for helping learners assess their progress and identify areas for improvement (Lui & Andrade, 2022; Pangarso & Istiyono, 2022). Affective feedback provides emotional support, enabling a feeling of encouragement and motivation in students (Câmpean et al., 2024). Both types of feedback are necessary for improving cognitive and emotional sides of the learning process, which in turn enables students' personal development and academic success (Agusnaya et al., 2023; Gan et al., 2023; Wibowo & Saliman, 2025). Grasping the connection between these types of feedback and their impact on motivation is critical to developing educational approaches that would ensure successful learning (Muzayana, 2024; Nirmala et al., 2025; Zepeda et al., 2023).

Research shows that effective feedback can increase motivation, but the interaction between these two types of feedback and their impact on individual self-regulation still needs to be studied further (Duijnhouwer et al., 2012; Straub et al., 2023). Previous research indicates that positive feedback, both cognitive and affective, can increase students' self-confidence and motivation, but the mechanisms of this interaction are not fully understood (Pornpattananangkul & Nusslock, 2016; Stobbeleir et al., 2010). Therefore, it is important to investigate how these two types of feedback can be integrated to develop a learning environment that is more conducive and efficient.

Personal growth and understanding are not solely the result of content mastery but emerge from how students internalize feedback, regulate their learning process, and develop sustained motivation (Brenner, 2022; Nurjannah et al., 2025). Self-regulation is also an important element that can mediate the relationship between feedback and motivation. Individuals who have good self-regulation skills are more likely to utilize feedback to improve their performance (Huang et al., 2023; Mei et al., 2018). Research shows that self-regulation not only facilitates the acceptance of feedback but also contributes to the achievement of higher learning goals (Freeman & Ambady, 2011; Wong et al., 2020). However, the literature is still lacking in explaining how self-regulation is influenced by the type of feedback, as well as its impact on motivation, personal growth, and understanding.

This study employs Social Cognitive Theory as the primary theoretical framework, emphasizing the reciprocal interaction between personal factors, behavior, and environmental influences in the learning process (Nabavi & Bijandi, 2011). Originally developed by Bandura, this theory offers a comprehensive perspective for understanding how students respond to feedback, build motivation, and regulate their learning through observation and self-reflection. Moreover, there are several other theories incorporated within the research to enhance the operationalization of constructs such as: Feedback Intervention Theory (Kluger & DeNisi, 1996), which helps explain emotions and emotion regulation; and Self-Determination Theory (Pekrun, 2006) to explain affective responses and emotional regulation, and Self-Determination Theory (Ryan & Deci, 2000) which forms the basis of intrinsic motivation, which leads to self-regulation and hence growth and learning. All of these theories serve as the basis for a strong conceptual framework to explore the interaction of feedback and motivation.

Based on the identified research gap, this study aims to examine the relationships among Cognitive Feedback, Affective Feedback, Motivation, Self-Regulation, and Personal Growth and Understanding using a PLS-SEM approach. Specifically, this study investigates the direct effects of Cognitive Feedback, Affective Feedback, and Motivation on Self-Regulation, the effect of Self-Regulation on Personal Growth and Understanding, and the mediating role of Self-Regulation in these relationships. The findings are expected to contribute to the development of more effective feedback strategies that integrate cognitive and affective dimensions to enhance students' personal growth and learning outcomes. Accordingly, the following research questions are addressed.

1. How does Cognitive Feedback affect Self-Regulation?
2. How does Affective Feedback affect Self-Regulation?
3. How does Motivation affect Self-Regulation?
4. How does Self-Regulation affect Personal Growth and Understanding?
5. Does Self-Regulation mediate the effect of Cognitive Feedback, Affective Feedback, and Motivation on Personal Growth and Understanding?

METHOD

Research Approach and Design

This study applied a quantitative approach with a cross-sectional design (Dweck & Yeager, 2019). This research was conducted to understand the interaction between cognitive, affective and motivational feedback in enhancing personal growth, focusing on the role of self-regulation. This approach facilitated gathering data from a broader population within a limited timeframe, enabling the study to present a concise representation of the relationships among the examined variables (Cañabate et al., 2018).

Population and Sample

The participants were those who were involved in the process of learning. Purposive sampling was used to have active students in learning activities since the interaction of cognitive and affective feedback and its ability to boost motivation was explored in terms of self-development (Basdogan & Bonk, 2023). The study sample size is 450 participants. The participants were purposively chosen among those who were actively learning and had been provided with feedback during the process of learning online. The method of sampling used can result in selection and self-selection biases, as only those who are interested in the topic and are digitally active will be reached. Data were collected through an online questionnaire created on Google Forms. Participants were notified about the study and agreed to participate by ticking an agreement box. The sample size was determined based on general guidelines considering the complexity of the model and the number of indicators used (Hair et al., 2021; Pan, 2020). Although adequate for statistical analysis, these findings should be interpreted with caution when generalizing beyond the specific context of the study.

Variables and Measures

The study includes five main variables: independent variables consisting of Cognitive Feedback with 14 items (CF1-CF14), Affective Feedback with 9 items (AF1-AF9), and Motivation with 7 items (M1-M7); dependent variable Personal Growth and Understanding with 5 items (PGU1-PGU5); and mediating variable Self-Regulation, which has 6 items (SR1-SR6). Each variable is explained in detail through the operational definitions presented in Table 1.

Table 1. Definition of Variable

No	Variable	Definition
1	Cognitive Feedback (CF)	Information provided to learners to help them understand and improve their cognitive processes and strategies (Byrne et al., 2020).
2	Affective Feedback (AF)	Emotional responses given to learners that influence motivation and engagement (Doorn et al., 2020).
3	Motivation (M)	Internal and external factors that drive interest and commitment to tasks or goals (Begishev et al., 2023) .
4	Self-Regulation (SR)	The capacity to regulate one's thoughts, feelings, and actions in pursuit of achieving long-term objectives (Braund & Timmons, 2021).
5	Personal Growth and Understanding (PGU)	The ongoing process of self-improvement and self-awareness through learning (Dhania et al., 2021).

Data Collection Technique

A questionnaire using a five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree) was used to collect data in this study, where each question was designed to assess indicators of each of the variables under study. Although the five-point Likert scale yields ordinal data, PLS-SEM is appropriate for this analysis. As noted by Hair et al. (2021), PLS-SEM can handle ordinal data, particularly with five or more categories, as it approximates interval-level properties and supports robust model estimation. Employing a five-point Likert scale is a widely accepted approach in survey research, as it facilitates a detailed comprehension of respondents' views and attitudes (Kusmaryono & Wijayanti, 2022). This scale facilitates the measurement of latent constructs by providing a range of responses that can be quantitatively analyzed (Abdelwahid et al., 2024).

Data Analysis

The gathered data will undergo analysis through the application of the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, as this method is capable of estimating complex relationships between latent variables and is suitable for small sample sizes without requiring normality assumptions for the data (Amusa & Hossana, 2024). Data analysis will be conducted using SmartPLS software, which involves two main stages: the evaluation of the outer model and the analysis of the inner model (Jacqueline et al., 2024). The overall research procedure is summarized in Figure 1.

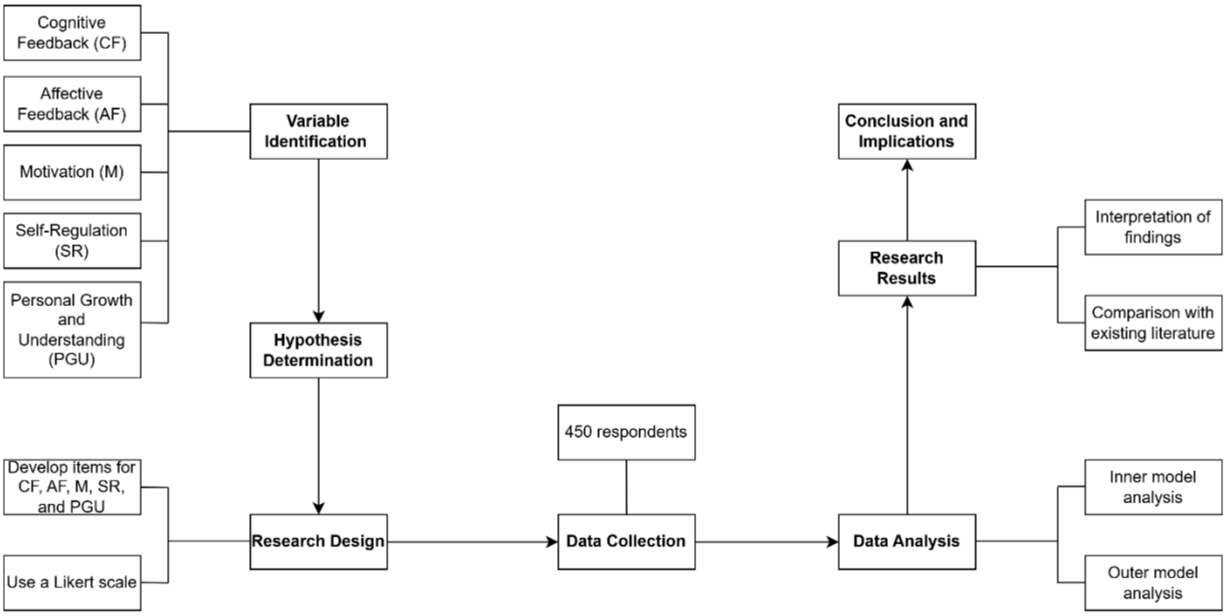

Figure 1. Research Procedure

The research procedure began with identifying the main constructs based on the theoretical framework, followed by developing the research hypotheses and designing the research instrument. Data were subsequently collected through an online questionnaire and analyzed using PLS-SEM. Finally, the structural relationships were interpreted to formulate conclusions and practical implications. The PLS-SEM analysis consisted of two stages, namely evaluation of the measurement model (outer model) and evaluation of the structural model (inner model).

Outer Model

During the outer model phase, this step is crucial for assessing the validity and reliability of latent construct measurements (Leoparjo et al., 2023). The outer model test is also known as the measurement mode (Dharma et al., 2021). The outer model illustrates the connection between latent constructs (unobservable variables) and their measured indicators (observable variables). This discussion focuses on aspects such as convergent validity and construct reliability (Wu & Irving, 2020). Convergent validity measures how well indicators correlate with each other in measuring a construct. To assess convergent validity, essential indicators like Outer Loading and Average Variance Extracted (AVE) are utilized (Wang et al., 2023). An acceptable Outer Loading value is above 0.70, indicating that the indicator significantly contributes to the latent construct (Rusaitis et al., 2021). Meanwhile, an acceptable AVE value is ≥ 0.50, indicating that more than 50% of the variance in the indicator is explained by the construct (Levshov et al., 2015). On the other hand, construct reliability refers to the internal consistency of indicators in measuring the latent construct (Dewi et al., 2021). This ensures that indicators consistently reflect the same construct throughout the model (Wong et al., 2020). Two main metrics are used to assess construct reliability in PLS-SEM: Composite Reliability (CR) and Rho_A (Scharnowski & Kähler, 2020). Acceptable values for CR and Rho_A are ≥ 0.70, indicating adequate internal consistency (Nakanishi et al., 2022). Furthermore, discriminant validity in PLS-SEM measures the extent to which constructs in the model differ significantly from each other (Lysak & Song, 2020). Discriminant validity is evaluated using the Heterotrait-Monotrait Ratio (HTMT), with acceptable HTMT values being below 0.85 or 0.90, indicating that the constructs in the model are truly distinct from one another (Irving et al., 2018).

Inner Model

At the inner model stage, this component is crucial as it focuses on the relationships between latent variables within a model (Schumacher & Muêller, 2021). The inner model analyzes the interactions and reciprocal influences among latent constructs, typically representing independent, mediator, and dependent variables in a study (Prasetiyo et al., 2023). Hypothesis testing is conducted through the analysis of Path Coefficients, T-Statistics, and P-Values (Hemrungrojn et al., 2022). Significant Path Coefficients generally exhibit T-Statistics values exceeding 1.96 at the 5% significance level, and the corresponding P-Values are below 0.05, indicating that the relationships between variables are not due to chance and are statistically significant (Keller, 2021).

Based on the theories discussed earlier, this research will formulate a structural model that investigates the relationships between cognitive feedback, affective feedback, and motivation, which affect the growth and understanding of the learners. Self-regulation is one of the important mediators within the structural model, as it connects feedback from the outside world with internal motivation in terms of holistic learning experience. Growth and understanding can be perceived as a single outcome, including self-awareness, emotional stability, reflective thought, and meaningful application of knowledge. It is assumed that cognitive and affective feedback have a positive impact on self-regulation (H1, H2), and motivation improves students' self-regulation (H3). As a result, self-regulation promotes growth and understanding of students (H4, H5). Figure 2 represents the proposed conceptual model.

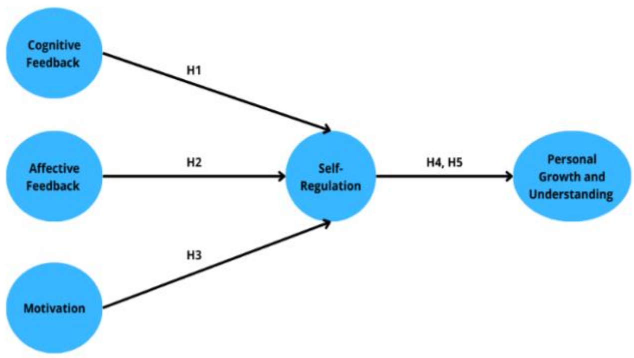

Figure 2. The Proposed Model in This Study

Hypothesis:

H_1 : Cognitive Feedback positively and significantly impacts Self-Regulation.
H_2 : Affective Feedback positively and significantly impacts Self-Regulation.
H_3 : Motivation has a substantial positive effect on Self-Regulation.
H_4 : Self-Regulation significantly and positively influences Personal Growth and Understanding.
H_5 : Self-Regulation acts as a mediator between Cognitive Feedback, Affective Feedback, Motivation, and Personal Growth and Understanding.
H_{5a}: Self-Regulation mediates the effect of Cognitive Feedback on Personal Growth and Understanding.
H_{5b}: Self-Regulation mediates the effect of Affective Feedback on Personal Growth and Understanding.
H_{5c}: Self-Regulation mediates the effect of Motivation on Personal Growth and Understanding.

RESULTS AND DISCUSSION

Demographic Analysis

The total sample size for this study consists of 450 respondents. The demographic information of the respondents is summarized in the table below. This analysis includes key variables such as gender distribution, age, academic semester, and levels of digital technology experience.

Table 2. Demographic Analysis

Category	Subcategory	Frequency	Percentage (%)
Gender	Male	181	40.22
	Female	269	59.78
Age	17	8	1.78
	18	93	20.67
	19	197	43.78
	20	111	24.67
	21	33	7.33
	22	8	1.78
Semester	II	184	40.89
	IV	227	50.44
	VI	37	8.22
	VIII	2	0.44
Experience	Beginner	29	2.22
	Intermediate	225	41.33
	Advanced	186	50.00
	None	10	6.44

The demographic table shows that the majority of respondents are female (59.78%), with a dominant age of 19 (43.78%) and 20 (24.67%). Most are in the fourth semester (50.44%) and the second semester (40.89%). In terms of experience, most respondents are at the advanced level (50.00%) and intermediate level (41.33%), while a small percentage are at the beginner level (2.22%) or have no experience (6.44%). This data portrays the respondents as predominantly young females, generally in the early to mid-stages of their studies, with relatively high technological skills.

Outer Model

Convergent Validity and Reliability

The findings regarding the evaluation of several latent constructs in the PLS-SEM framework are provided in Table 3. The list of these constructs includes Cognitive Feedback (CF), Affective Feedback (AF), Motivation (M), Self-Regulation (SR), and Personal Growth and Understanding (PGU). All these constructs can be described through their indicators, which were evaluated through the use of outer loadings, rho_A criteria, CR, and AVE.

Table 3. Outer Loading, Rho_A Metrics, Composite Reliability (CR), and Average Variance Extracted (AVE)

Construct and Items	Outer Loading	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Cognitive Feedback (CF)				
CF1	0.699	0.954	0.958	0.622
CF2	0.779			
CF3	0.781			
CF4	0.797			
CF5	0.799			
CF6	0.806			
CF7	0.836			
CF8	0.815			
CF9	0.782			
CF10	0.805			
CF11	0.773			
CF12	0.827			
CF13	0.753			
CF14	0.778			

Construct and Items	Outer Loading	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Affective Feedback (AF)				
AF1	0.802	0.931	0.940	0.636
AF2	0.717			
AF3	0.775			
AF4	0.792			
AF5	0.825			
AF6	0.779			
AF7	0822			
AF8	0.817			
AF9	0.842			
Motivation (M)				
M1	0.788	0.921	0.934	0.671
M2	0.855			
M3	0.815			
M4	0.878			
M5	0.735			
M6	0.833			
M7	0.822			
Self-Regulation (SR)				
SR1	0.637	0.846	0.883	0.558
SR2	0.823			
SR3	0.785			
SR4	0.673			
SR5	0.779			
SR6	0.768			
Personal Growth and Understanding (PGU)				
PGU1	0.812	0.892	0.921	0.699
PGU2	0.819			
PGU3	0.863			
PGU4	0.860			
PGU5	0.827			

In assessing the convergent validity and reliability, it is essential to ensure that the measurement tools provide accurate and consistent measurement of the constructs of interest. While validity is concerned with the confirmation that the variables measure the concepts properly, reliability indicates consistency in the responses given by the respondents. Hair et al. (2021) argue that outer loadings should preferably be more than 0.70, Composite Reliability (CR) should be above 0.70 to achieve internal consistency, and Average Variance Extracted (AVE) should be higher than 0.50 to indicate enough variance explained by each construct. The construct of cognitive feedback (CF) is reliable, and its outer loadings fall between 0.699 and 0.836. Even though CF1 has a relatively low outer loading of 0.699, the entire CR value of 0.958 and AVE value of 0.622 meet the suggested levels, which means that the CF construct passes the test of reliability and convergent validity. Affective feedback (AF) is a reliable construct with outer loadings between 0.717 and 0.842, CR of 0.940, and AVE of 0.636.

Similarly, M also meets the desired threshold levels, with outer loadings of 0.735 to 0.878, CR of 0.934, and AVE of 0.671. On the other hand, self-regulation (SR) is shown to have outer loadings from 0.637 to 0.823, with a CR of 0.883 and an AVE of 0.558. In spite of the fact that SR1 shows lower outer loading (0.637), there can be a confirmation of the reliability and validity of this construct. Finally, PGU shows excellent reliability, with outer loadings from 0.812 to 0.863, CR of 0.921, and AVE of 0.699 – all those figures exceed recommended thresholds. While CF1, SR1, and SR4 show somewhat lower outer loadings (lower than the recommended value of 0.70), the inclusion of these measures into the model was justified by their theoretical importance and context-relatedness for these constructs. It ensured the content coverage based on the measurement dimensions originally designed. Moreover, the exclusion of these measures did not increase the Composite Reliability or AVE values of the model. As recommended by Hair et al. (2021), those indicators which show loadings above 0.60 can still be considered appropriate if they add significant value to the construction and do not undermine the quality of measurement. Having fulfilled all these requirements, the instruments applied within this study can be viewed as reliable and valid, thus forming an excellent basis for the interpretation of research results. These findings prove the validity and reliability of all constructs used in this study.

Discriminant Validity

The results of the Heterotrait-Monotrait Ratio (HTMT) test, which evaluates discriminant validity across multiple latent constructs in the PLS-SEM model, are summarized in Table 4. The constructs examined include Cognitive Feedback (CF), Affective Feedback (AF), Motivation (M), Self-Regulation (SR), and Personal Growth and Understanding (PGU).

Table 4. Heterotrait-Monotrait Ratio

	AF	CF	M	PGU	SR
AF					
CF	**0.869**				
M	0.733	**0.781**			
PGU	0.817	0.766	**0.703**		
SR	0.741	0.737	0.814	**0.817**	

Based on Table 4, the Heterotrait-Monotrait Ratio (HTMT) above, the discriminant validity analysis shows that most construct pairs have HTMT values within acceptable limits. The following pairs show HTMT values below 0.90: AF-M (0.733), AF-PGU (0.817), CF-M (0.781), CF-PGU (0.766), CF-SR (0.737), and M-PGU (0.703). These values indicate sufficient discriminant validity among these constructs, meaning each construct can be considered distinct from the others without issues concerning discriminant validity.

However, some construct pairs have HTMT values close to the upper threshold of 0.90. For instance, the AF-CF pair has an HTMT value of 0.869, which approaches the threshold yet remains acceptable. This suggests some similarity between Affective Feedback (AF) and Cognitive Feedback (CF), although they can still be considered distinct. Additionally, the SR-PGU pair has an HTMT value of 0.817, which, while not as high, is still near the threshold, indicating slight similarity between Self-Regulation (SR) and Personal Growth and Understanding (PGU).

Overall, these results indicate that each construct in this model possesses adequate discriminant validity and can be regarded as distinct entities, although some pairs show a higher degree of similarity.

Inner Model

Hypothesis Test

Table 5, showing the hypothesis testing results from the PLS-SEM analysis, offers a detailed overview of the relationships between latent constructs, incorporating path coefficients, T-statistics, p-values, and the final determination of the significance of these relationships. PLS-SEM, as an increasingly popular analysis method, allows researchers to evaluate structural and measurement models simultaneously, which is particularly important in the context of social and behavioural research (Hair et al., 2021).

Table 5. Hypothesis Test

	Hypothesis	Path Coef	T Statistics	P Values	Decision
H1	CF->SR	0.198	2.420	0.016	Positive and Significant
H2	AF->SR	0.176	2.784	0.006	Positive and Significant
H3	M->SR	0.471	7.808	0.000	Positive and Significant
H4	SR->PGU	0.707	21.330	0.000	Positive and Significant

H5a	CF->SR->PGU	0.140	2.374	0.018	Positive and Significant
H5b	AF->SR->PGU	0.125	2.645	0.008	Positive and Significant
H5c	M->SR->PGU	0.334	7.872	0.000	Positive and Significant

Based on Table 5 Hypothesis Testing, it can be interpreted that the hypothesis H_1 confirms that Cognitive Feedback (CF) has a significant and positive influence on Self-Regulation (SR), with a path coefficient of 0.198, a T-Statistic of 2.420, and a P-Value of 0.016. This finding aligns with Feedback Intervention Theory (FIT) proposed by Kluger & DeNisi (1996), which posits that feedback providing specific performance-related information can enhance students' self-regulation. Cognitive feedback enables students to better understand their progress, thereby improving their ability to adjust learning strategies accordingly (Eccles & Wigfield, 2002).

Additionally, this result is supported by Self-Regulated Learning Theory (Zimmerman, 2000), which emphasizes that learners who receive structured cognitive feedback can develop more effective self-regulation strategies. When students are aware of their learning processes through feedback, they can refine their learning approaches, set goals more effectively, and enhance their academic performance (Eccles & Wigfield, 2002). These findings underscore the crucial role of cognitive feedback in fostering self-regulation by providing structured insights that empower students to take control of their learning (Arfianti & Azmi, 2021).

Next, hypothesis H_2 demonstrates that Affective Feedback (AF) has a significant and positive impact on Self-Regulation (SR), as evidenced by a path coefficient of 0.176, a T-Statistic of 2.784, and a P-Value of 0.006. This finding is in line with the Control-Value Theory of Achievement Emotions (Pekrun, 2006), which posits that affective feedback fostering positive emotions enhances self-regulation by strengthening students' perceptions of control and the value of academic tasks. When students receive supportive emotional feedback, they are more likely to remain engaged, regulate their emotions effectively, and persist in achieving their learning goals.

Furthermore, this result aligns with Social Cognitive Theory by Bandura (Nabavi & Bijandi, 2011), which emphasizes that emotional support in feedback contributes to increased self-efficacy, enabling students to develop better self-regulation skills. When students feel emotionally supported, their confidence in their academic abilities improves, leading to a more proactive approach to self-regulation and learning (Pekrun, 2006). These findings highlight the essential role of affective feedback in promoting self-regulation, as it not only helps students manage emotional challenges but also fosters motivation and persistence in academic settings (Tonni et al., 2023).

Hypothesis H_3 demonstrates that Motivation (M) significantly and positively impacts Self-Regulation (SR), with a path coefficient of 0.471, a T-Statistic of 7.808, and a P-Value of 0.000. This aligns with Self-Determination Theory (SDT) by Deci & Ryan (1985), which states that intrinsic motivation, driven by competence, autonomy, and social connection, enhances self-regulation in learning. Similarly, Expectancy-Value Theory (Eccles & Wigfield, 2002) explains that students who value academic tasks and believe in their success are more likely to apply self-regulation strategies. These findings emphasize motivation's role in fostering self-directed learning and academic persistence (Talib et al., 2023; Yaseen et al., 2023).

Hypothesis H_4 indicates that Self-Regulation (SR) significantly and positively influences Personal Growth and Understanding (PGU), supported by a path coefficient of 0.707, a T-Statistic of 21.330, and a P-Value of 0.000. This finding suggests that students with strong self-regulation skills tend to experience greater improvements in both personal growth and academic understanding. According to Mubuuke et al. (2017), self-regulation plays a crucial role in structuring students' learning experiences, ensuring they actively engage in their academic progress and achieve meaningful learning outcomes. Additionally, Carless & Boud (2018) emphasize that student feedback literacy enhances self-regulation, allowing students to effectively interpret and utilize feedback for continuous personal and academic development. These perspectives align with the results of this study, reinforcing the idea that self-regulated students are more likely to accomplish their learning objectives, ultimately fostering deeper personal growth and understanding (Dillah et al., 2023; Katsantonis & McLellan, 2023).

Hypotheses H_{5a}, H_{5b}, and H_{5c} demonstrates that Self-Regulation (SR) serves as a mediator for the impact of Cognitive Feedback (CF), Affective Feedback (AF), and Motivation (M) on Personal Growth and Understanding (PGU). H_{5a} reveal that the effect of Cognitive Feedback (CF) on Personal

Growth and Understanding (PGU) is mediated by Self-Regulation (SR), as shown by a path coefficient of 0.140, a T-Statistic of 2.374, and a P-Value of 0.018. This suggests that cognitive feedback indirectly fosters personal growth by strengthening self-regulation. Feedback Intervention Theory (FIT) by Kluger & DeNisi (1996) supports this, stating that feedback providing structured performance insights enhances self-regulation and learning effectiveness. Additionally, Hattie & Timperley (2007) emphasize that effective feedback strengthens self-regulation by offering clear performance-related insights, enabling students to develop strategies for managing their learning. Similarly, Spooner et al. (2023) highlights that students who actively engage with feedback exhibit stronger self-regulation abilities, which ultimately contribute to their academic and personal development. Empirical research further supports these findings, demonstrating that cognitive feedback improves students' awareness of their learning process, fostering meaningful learning experiences and personal growth (Li & Zhang, 2021).

H_{5b} demonstrates that Self-Regulation (SR) mediates the relationship between Affective Feedback (AF) and Personal Growth and Understanding (PGU), as evidenced by a path coefficient of 0.125, a T-Statistic of 2.645, and a P-Value of 0.008. This finding indicates that affective feedback, which provides emotional support, helps students develop self-regulation, which in turn enhances their personal growth. Control-Value Theory of Achievement Emotions (Pekrun, 2006) suggests that positive affective feedback reinforces students' perceptions of control and academic value, which enhances their ability to self-regulate. Furthermore, Colquhoun et al. (2017) propose that self-regulation and goal-setting theories provide a theoretical framework for understanding how feedback influences students' ability to regulate their learning. Further argue that feedback literacy plays a critical role in developing self-regulation skills, as students who understand and apply feedback effectively are better equipped to manage their learning and personal development (Carless & Boud, 2018). Empirical studies also show that emotional support through affective feedback fosters self-confidence and resilience, ultimately promoting personal growth and deeper understanding (Arfianti & Azmi, 2021).

H_{5c} highlights that Self-Regulation (SR) acts as a mediator between Motivation (M) and Personal Growth and Understanding (PGU), as reflected by a path coefficient of 0.334, a T-Statistic of 7.872, and a P-Value of 0.000. This indicates that highly motivated students are more likely to develop self-regulation skills, which in turn enhances their personal growth. Self-Determination Theory (SDT) by Deci & Ryan (1985) explains that intrinsic motivation driven by the need for competence, autonomy, and social relatedness enhances self-regulation in learning. Additionally, Expectancy-Value Theory Eccles & Wigfield (2002) posits that when students perceive academic tasks as valuable and believe in their success, they are more likely to implement self-regulation strategies. Further assert that feedback plays a vital role in promoting structured and self-directed learning, reinforcing the idea that motivation-driven self-regulation leads to academic and personal success (Mubuuke et al., 2017). Moreover, Carless & Boud (2018) emphasize that students who actively engage with feedback and recognize its value are more likely to regulate their learning effectively, further supporting their personal and intellectual development. Empirical research also confirms that intrinsic motivation enhances self-regulation strategies, enabling students to manage their learning independently and achieve long-term academic success (Wangid, 2022; Yaseen et al., 2023).

Overall, these hypothesis test results show that Cognitive Feedback, Affective Feedback, and Motivation significantly impact Self-Regulation, which in turn affects Personal Growth and Understanding. Research highlights of self-regulation as an intermediary connecting feedback, motivation, and students' personal growth, highlighting its importance in advancing both the learning process and individual development (Tubaon & Palma, 2022). Further investigations are required to delve into the foundational mechanisms of these interactions and to uncover additional factors that could support the enhancement of self-regulation and personal growth among learners. The findings of this study align with and extend previous research on the role of feedback and motivation in fostering self-regulation and personal growth. Zimmerman (2000) theory highlights that constructive feedback enhances learners' ability to set goals and reflect, while our model expands this by combining cognitive, affective, and motivational components, unlike prior studies that focused narrowly on one type of feedback (Brandmo & Gamlem, 2025; Carless & Boud, 2018; Duijnhouwer et al., 2012).

In many current classroom practices, feedback tends to be generic and lacks emotional nuance, which may lead to missed opportunities in promoting student development (Glassner & Back, 2020). This study highlights the importance of integrating cognitive feedback, such as clear and timely performance information, with affective components like praise and empathetic responses to effectively enhance students' motivation and self-regulation. Educators are encouraged to adopt dialogic feedback approaches that not only deliver information but also support students emotionally (Brandmo & Gamlem, 2025). Furthermore, the findings underscore the future potential of adaptive learning technologies. As education increasingly integrates digital tools, feedback systems such as AI-based platforms should be designed to provide personalized responses that address both cognitive and emotional learner needs, thereby supporting deeper personal growth and self-directed learning.

LIMITATIONS

There are certain limitations to this study. The first limitation is that the sample consisted only of university students recruited using the purposive sampling technique, which may result in selection bias and thus make it difficult for the results to be generalized across different education levels. The second limitation is that the cross-sectional design used cannot facilitate drawing of causal conclusions and does not allow observation of changes over time. Moreover, the data obtained were self-reported by the participants and may be subject to some biases, such as social desirability. Finally, there may be cultural factors that affect the perception of feedback and motivation, and should be taken into account when interpreting the results.

CONCLUSION

Through the findings of this research, we can observe that the impact of Cognitive Feedback, Affective Feedback, and Motivation is very significant in developing the Self-Regulation behavior that is important in the process of Personal Growth and Understanding. This research emphasizes the importance of integrating cognitive and affective feedback in educational settings to improve learners' self-regulation and overall personal growth. Self-Regulation becomes a mediating element in the process where the influence of feedback and motivation becomes more effective in contributing to the process of personal development.

Despite the valuable information that has been revealed through the research, some limitations need to be mentioned. First of all, due to the cross-sectional approach adopted, it becomes impossible to trace the dynamics or evolution over time. Moreover, the use of self-reporting can lead to response bias. In the future, it would be useful for researchers to apply other approaches, such as longitudinal or experimental designs, and to increase the diversity of the study sample.

AUTHOR CONTRIBUTIONS

The research design and data collection were the responsibility of ADNA and SSa. MMF did the statistical analysis and was largely involved in developing the methodology of the research. The drafting of the manuscript and the discussion sections were done by KPP and DFS; however, SSo critically revised the manuscript and made theoretical contributions. All authors have been involved in the review and approval of the final manuscript.

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REFERENCES

Abdelwahid, H. A., Dahlan, H. M., Mojemamy, G. M., Al-Harbi, T. J., Indarkiri, N. Y., & Tourkmani, A. M. (2024). Developing and standardizing a tool to assess the health education needs of diabetic patients at Jazan Armed Forces Hospital. *Research Square*. Advance online publication. https://doi.org/10.21203/rs.3.rs-3758790/v1

Agusnaya, N., Wahid, A., Akbar, M., Hidayat, W. M., Sanatang, S., Soeharto, S., & Lavicza, Z. (2024). Enhancing digital learning in higher education: The mediating role of academic self-efficacy in motivation and engagement. *Online Learning in Educational Research (OLER), 4(*2), 167–183. https://doi.org/10.58524/oler.v4i2.505

Amusa, L. B., & Hossana, T (2024). An empirical comparison of some missing data treatments in PLS-SEM. *PLOS ONE, 19*(1), e0297037. https://doi.org/10.1371/journal.pone.0297037

Arfianti, K., & Azmi, K. R. (2021). Self-regulated learning (SRL): Skills in improving learning motivation. *Konseli: Jurnal Bimbingan dan Konseling (E-Journal), 8*(2). https://doi.org/10.24042/kons.v8i2.9958

Basdogan, M. & Bonk, C.(2023). Navigating online learning through “technological frames.” *Online Learning, 27*(4). https://doi.org/10.24059/olj.v27i4.4030

Begishev, I., Asli, M. R., Denisovich, V., Majorov, A., & Sergeyev, A. (2023). Issues of personal data protection through the lens of sustainable development and law. *E3S Web of Conferences, 449*, 03005. https://doi.org/10.1051/e3sconf/202344903005

Brandmo, C., & Gamlem, S. M. (2025). Students’ perceptions and outcome of teacher feedback: A systematic review. *Frontiers in Education, 10*, 1572950. https://doi.org/10.3389/feduc.2025.1572950

Braund, H., & Timmons, K. (2021). Operationalization of self-regulation in the early years: Comparing policy with theoretical underpinnings. *International Journal of Child Care and Education Policy, 15*(1). https://doi.org/10.1186/s40723-021-00085-7

Brenner, C. A. (2022). Self-regulated learning, self-determination theory and teacher candidates’ development of competency-based teaching practices. *Smart Learning Environments, 9*(1), 3. https://doi.org/10.1186/s40561-021-00184-5

Byrne, A., Baldwin, A., & Harvey, C. (2020). Whose centre is it anyway? Defining person-centred care in nursing: An integrative review. *PLOS ONE, 15*(3), e0229923. https://doi.org/10.1371/journal.pone.0229923

Câmpean, A., Bocoș, M., Roman, A., Rad, D., Crișan, C., Maier, M., Tăușan-Crișan, L., Triff, Z., Triff, D.-G., Mara, D., Mara, E.-L., Răduț-Taciu, R., Todor, I., Baciu, C., Neacșu, M.-G., Dumitru, I., Colareza, C. C., & Roman, C. E. (2024). Examining teachers’ perception on the impact of positive feedback on school students. *Education Sciences, 14*(3), 257. https://doi.org/10.3390/educsci14030257

Cañabate, D., Serra, L., Niell, M., Nogué, L., Serra, T., & Colomer, J. (2018). Sustainable peer feedback in higher education: Category-driven analysis on pre-service students’ perceptions. *Preprints*. https://doi.org/10.20944/preprints201810.0436.v1

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Colquhoun, H., Carroll, K., Eva, K. W., Grimshaw, J., Ivers, N., Michie, S., Sales, A. E., & Brehaut, J. (2017). Advancing the literature on designing audit and feedback interventions: Identifying theory-informed hypotheses. *Implementation Science, 12*, 117. https://doi.org/10.1186/s13012-017-0646-0

Dewi, L., Tentama, F., & Diponegoro, A. M. (2021). Subjective well-being: Mental health study among students in the Islamic boarding school. *International Journal of Public Health Science (IJPHS), 10*(1). https://doi.org/10.11591/ijphs.v10i1.20610

Dhania, D. R., Suryanto, S., Suhariadi, F., & Fajrianthi, F. (2021). Personal growth initiative of millennial women leaders in Indonesia: A qualitative study. *Journal of Educational, Health and Community Psychology, 10*(1). https://doi.org/10.12928/jehcp.v10i1.17415

Dharma, I. W. M. S., Sari, D. P., & Rahmat, B. (2021). Validity and reliability test of the Short Form-36 (SF-36) item health survey in Indonesian version of post-heart attack patients in Mataram City.

In *Advances in Health Sciences Research* (Vol. 39). Atlantis Press. https://doi.org/10.2991/ahsr.k.220206.066

Dillah, D., Subramaniam, S., Abd Hamid, N. B., Subramaniam, N., Afrin, J. F., & Rahmat, N. H. (2023). Investigating pre-university students' motivation to learn and their use of self-regulated learning strategies. *International Journal of Academic Research in Business and Social Sciences, 13*(10). https://doi.org/10.6007/IJARBSS/v13-i10/18961

Ding, N. (2025). Analysis of the role of teacher feedback in students' cognitive engagement. *International Journal of Education and Humanities, 18*(1), 279–283. https://doi.org/10.54097/6qe8s854

Doorn, K. A., Garay, C. J., Etchebarne, I., Kamsteeg, C., & Roussos, A. (2020). Psychotherapy for personal growth? A multicultural and multitheoretical exploration. *Journal of Clinical Psychology, 76*(10), 1895–1912. https://doi.org/10.1002/jclp.22942

Duijnhouwer, H., Prins, F. J., & Stokking, K. M. (2012). Feedback providing improvement strategies and reflection on feedback use: Effects on students' writing motivation, process, and performance. *Learning and Instruction, 22*(3), 171–184. https://doi.org/10.1016/j.learninstruc.2011.10.003

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A view from two eras. *Perspectives on Psychological Science, 14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*, 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Freeman, J. B., & Ambady, N. (2011). A dynamic interactive theory of person construal. *Psychological Review, 118*(2), 247–279. https://doi.org/10.1037/a0022327

Gan, Z., Liu, F., & Nang, H. (2023). The role of self-efficacy, task value, and intrinsic and extrinsic motivations in students' feedback engagement in English learning. *Behavioral Sciences, 13*(5), 428. https://doi.org/10.3390/bs13050428

Glassner, A., & Back, S. (2020). Pioneers of heutagogy. In A. Glassner & S. Back (Eds.), *Exploring heutagogy in higher education* (pp. 93–103). Springer Singapore. https://doi.org/10.1007/978-981-15-4144-5_7

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112. https://doi.org/10.3102/003465430298487

Hemrungrojn, S., Amrapala, A., & Maes, M. (2022). Construction of a short version of the Montreal Cognitive Assessment (MoCA) rating scale using partial least squares analysis. *medRxiv*. Advance online publication. https://doi.org/10.1101/2022.05.05.22274726

Huang, Q., He, C., & Luo, J. (2023). Image super-resolution reconstruction based on residual convolution and double attention mechanism. *International Journal of Computer Applications Technology and Research, 12*(3), 1–5. https://doi.org/10.7753/IJCATR1203.1001

Irving, J. C. E., Cottaar, S., & Lekić, V. (2018). Seismically determined elastic parameters for Earth's outer core. *Science Advances, 4*(6), eaar2538. https://doi.org/10.1126/sciadv.aar2538

Jacqueline, G., Senjaya, Y. P. A., Firli, M. Z., & Yadila, A. B. (2024). Application of SmartPLS in analyzing critical success factors for implementing knowledge management in the education sector. *Aptisi Transactions on Management (ATM), 8*(1). https://doi.org/10.33050/atm.v8i1.2201

Katsantonis, I., & McLellan, R. (2023). Person-centred study on higher-order interactions between students' motivational beliefs and metacognitive self-regulation: Links with school language achievement. *PLOS ONE, 18*(7), e0289367. https://doi.org/10.1371/journal.pone.0289367

Keller, B. T. (2021). An introduction to factored regression models with Blimp. *Psych, 4*(1), 2. https://doi.org/10.3390/psych4010002

Kluger, A. N., & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin, 119*(2), 254–284. https://doi.org/10.1037/0033-2909.119.2.254

Kusmaryono, I., & Wijayanti, D. (2022). Number of response options, reliability, validity, and potential bias in the use of the Likert scale in education and social science research: A literature review. *International Journal of Educational Methodology, 8*(4), 625–637. https://doi.org/10.12973/ijem.8.4.625

Leoparjo, F., Harianto, E., Mas'ud, R., Ilyas, G. B., & Hasanah, Y. N. (2023). Assessing the effect of online learning service quality on customer retention through customer satisfaction as mediation variable in the culinary study program bachelor degree during the Covid-19 pandemic. *Jurnal Aplikasi Manajemen, 21*(2). https://doi.org/10.21776/ub.jam.2023.021.02.20

Levshov, D., Michel, T., Arenal, R., Tran, H.-N., Than, T. X., Paillet, M., Yuzyuk, Y. I., & Sauvajol, J.-L. (2015). Interlayer dependence of G-modes in semiconducting double-walled carbon nanotubes. *The Journal of Physical Chemistry C, 119*(32), 18749–18756. https://doi.org/10.1021/acs.jpcc.5b05888

Li, W., & Zhang, F. (2021). Tracing the path toward self-regulated revision: An interplay of instructor feedback, peer feedback, and revision goals. *Frontiers in Psychology, 11*, 612088. https://doi.org/10.3389/fpsyg.2020.612088

Lui, A. M., & Andrade, H. (2022). The next black box of formative assessment: A model of the internal mechanisms of feedback processing. *Frontiers in Education, 7*, 751548. https://doi.org/10.3389/feduc.2022.751548

Lysak, R. L., & Song, Y. (2020). Field line resonances in Jupiter's magnetosphere. *Geophysical Research Letters, 47*(18), e2020GL089473. https://doi.org/10.1029/2020GL089473

Mahmoudi, S., Jafari, E., Nasrabadi, H. A., & Liaghatdar, M. J. (2012). Holistic education: An approach for the 21st century. *International Education Studies, 5*(3), 178–186. https://doi.org/10.5539/ies.v5n3p178

Mei, S., Li, Q., Liu, X., & Zheng, Y. (2018). Monetary incentives modulate feedback-related brain activity. *Scientific Reports, 8*, 11934. https://doi.org/10.1038/s41598-018-30294-z

Mubuuke, A. G., Louw, A., & Van Schalkwyk, S. (2017). Self-regulated learning: A key learning effect of feedback in a problem-based learning context. *African Journal of Health Professions Education, 9*(1), 26–30. https://doi.org/10.7196/AJHPE.2017.v9i1.715

Muzayana, I. (2024). Systematic literature review on the implementation of the Pesantren Muadalah certificate policy in Indonesia. *Kharisma: Jurnal Administrasi dan Manajemen Pendidikan, 3*(2), 109–122. https://doi.org/10.59373/kharisma.v3i2.51

Nabavi, R. T., & Bijandi, M. S. (2011). *Bandura's social learning theory & social cognitive learning theory*

Nakanishi, H., Sakai N., & Kurahara K. (2022). Astrometry of water maser sources in the outer Galaxy with VERA. *Proceedings of the International Astronomical Union, 17*(S366), 120–123. https://doi.org/10.1017/S1743921323003010

Nirmala, P., Suhardi, I., Kaswar, A. B., Surianto, D. F., Fajar, M. B., Soeharto, S., & Lavicza, Z. (2025). Enhancing computational thinking skills through digital literacy and blended learning: The mediating role of learning motivation. *Online Learning in Educational Research (OLER), 5*(1), 9–24. https://doi.org/10.58524/oler.v5i1.504

Nurjannah, E., Mangesa, R. T., Fakhri, M. M., Fajar, M. B., Sanatang, S., & Arifiyanti, F. (2025). Enhancing digital learning outcomes: The combined impact of competence and psychological traits. *Online Learning in Educational Research (OLER), 5*(2), 277–288. https://doi.org/10.58524/oler.v5i2.513

Pan, X. (2020). Technology acceptance, technological self-efficacy, and attitude toward technology-based self-directed learning: Learning motivation as a mediator. *Frontiers in Psychology, 11*, 564294. https://doi.org/10.3389/fpsyg.2020.564294

Pangarso, Z. D., & Istiyono, E. (2022). Go formative for formative assessment feedback on the 10th graders' material comprehension and learning motivation. *Jurnal Ilmiah Pendidikan Fisika Al-Biruni, 11*(2). https://doi.org/10.24042/jipfalbiruni.v11i2.13754

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315–341. https://doi.org/10.1007/s10648-006-9029-9

Pornpattananangkul, N., & Nusslock, R. (2016). Willing to wait: Elevated reward-processing EEG activity associated with a greater preference for larger-but-delayed rewards. *Neuropsychologia, 91*, 141–162. https://doi.org/10.1016/j.neuropsychologia.2016.07.037

Prasetiyo, A. Y., Widodo, & Ratnawati, A. (2023). Concept and scale development of karimah work ambition. *Journal of Islamic Business and Management (JIBM), 13*(1). https://doi.org/10.26501/jibm/2023.1301-008

Rusaitis, L., Khurana, K. K., Kivelson, M. G., & Walker, R. J. (2021). Quasiperiodic 1-hour Alfvén wave resonances in Saturn's magnetosphere: Theory for a realistic plasma/field model. *Geophysical Research Letters, 48*(3), e2020GL090967. https://doi.org/10.1029/2020GL090967

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Scharnowski, S., & Kähler, C. J. (2020). Investigation of the base flow of a generic space launcher with dual-bell nozzle. *CEAS Space Journal, 12*(4), 555–569. https://doi.org/10.1007/s12567-020-00333-5

Schumacher, P. B., & Müller, G. (2021). Construct validity of the Braden Scale for predicting pressure sore risk in the long-term care setting: A structural equation modeling analysis of secondary data. *Research Square*. Advance online publication. https://doi.org/10.21203/rs.3.rs-134197/v1

Spooner, M., Larkin, J., Liew, S. C., Jaafar, M. H., McConkey, S., & Pawlikowska, T. (2023). "Tell me what is 'better'!" How medical students experience feedback, through the lens of self-regulated learning. *BMC Medical Education, 23*, 842. https://doi.org/10.1186/s12909-023-04842-9

Stobbeleir, K. E. M., Ashford, S. J., & Luque, M. S. (2010). Proactivity with image in mind: How employee and manager characteristics affect evaluations of proactive behaviours. *Journal of Occupational and Organizational Psychology, 83*(2), 347–369. https://doi.org/10.1348/096317909X479529

Straub, L., Lin, E., Tremonte-Freydefont, L., & Schmid, P. C. (2023). Individuals' power determines how they respond to positive versus negative performance feedback. *European Journal of Social Psychology, 53*(7), 1402–1420. https://doi.org/10.1002/ejsp.2985

Talib, F. E. A., Ris, E. Z. M., Kamaralzaman, S., Yusof, Y. M., Hashim, H., Mohamad Zubir, A. R., & Rahmat, N. H. (2023). Motivated learners: How do they use their self-regulated learning strategies? *International Journal of Academic Research in Business and Social Sciences, 13*(10). 356-370. https://doi.org/10.6007/IJARBSS/v13-i10/18781

Tonni, I., Fine, P., Leung, A., Louca, C., & Paganelli, C. (2023). Students' perceptions of tutor feedback: A pilot study. *Minerva Dental and Oral Science, 72*(1), 25–32. https://doi.org/10.23736/S2724-6329.22.04611-3

Tubaon, M., & Palma, R. (2022). Active reading style, student vocabulary learning strategies and self-regulated learning: A structural equation model on academic writing motivation and self-regulation. *Asian Journal of Education and Social Studies, 36*(4), 790–804. https://doi.org/10.9734/ajess/2022/v36i4790

Wang, X., Yu, Y., Deng, D., Mao, S., Wang, Y., Gu, H., Song, Y., Pang, F., Zhuang, L., Yang, S., He, X., & Wang, C. (2023). Alleviating orbital angular momentum mode coupling between two ring-cores with different materials in a photonic crystal fiber for optical communication. *Physica Scripta, 99*(1), 015505. https://doi.org/10.1088/1402-4896/ad16ce

Wangid, M. N. (2022). The role of self-motivation in self-regulated learning. *Psikopedagogia: Jurnal Bimbingan dan Konseling, 11*(1), 1–9. https://doi.org/10.12928/psikopedagogia.v11i1.14175

Wibowo, G. A., & Saliman. (2025). Gamification in online learning: A systematic review of engagement and learning outcomes in digital education. *Online Learning in Educational Research (OLER), 5*(2), 351–367. https://doi.org/10.58524/oler.v5i2.733

Wong, M., Chung, P., & Leung, K. (2020). Speed of processing and personality: The influence of personality and extrinsic feedback on the performance of cognitive tasks. *Behavioral Sciences, 10*(4), 76. https://doi.org/10.3390/bs10040076

Wu, W., & Irving, J. C. E. (2020). Array-based iterative measurements of travel times and their constraints on outermost core structure. *Journal of Geophysical Research: Solid Earth, 125*(3), e2019JB018162. https://doi.org/10.1029/2019JB018162

Yaseen, S., Aslam, S., Riaz, I., Shahzad, M., Peerzado, M. B., Manzoor, A., Amir, S. M., & Usman, M. (2023). Motivational determinants of self-regulated learning at the university level in Punjab, Pakistan.

Journal of Education and Social Studies, 4(3), 334–343. https://doi.org/10.52223/jess.2023.4334

Zepeda, C. D., Ortegren, F. R., & Butler, A. C. (2023). Learning from feedback in college courses: Student beliefs, practices, and preferences. *Applied Cognitive Psychology, 37*(5), 1234–1248. https://doi.org/10.1002/acp.4118

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7