The Impact of Academic Burnout on the Motivational Orientations of Learners of French as a Foreign Language: A PLS-SEM Approach

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ABSTRACT

With growing pressure in today's world, students are facing burnout from meeting academic demands. This may influence students' motivation and academic engagement, which causes growing concern in higher education. Therefore, this study is conducted to examine the influence of burnout on students' motivation by integrating the Job Demands–Resources Model and Expectancy–Value Theory. These relationships are then tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). A questionnaire consisting of three components including value, expectancy, and affective was distributed to 125 undergraduate students. The results were then analysed using SmartPLS, following a two-stage procedure involving measurement and structural model assessment. The findings revealed that the measurement model exhibited satisfactory reliability and validity across all constructs. Structural model results revealed that disengagement exerted significant effects on all three motivational components (value, expectancy, and affective), indicating its strong and consistent influence on students' motivational beliefs and emotional responses toward learning. Exhaustion, however, showed a more selective impact, significantly influencing expectancy but not value or affective components. Overall, the results suggest that motivational withdrawal affects students' motivation greater than emotional fatigue. These findings contribute to a more detailed understanding of how multiple aspects of burnout may affect students' motivation. The study also highlighted that PLS-SEM is useful in studying the complex relationship between psychological constructs. The results of this study contribute to addressing students' loss of interest and highlight the role of educators in supporting student motivation during lessons.

Keywords: Burnout, Motivation, Exhaustion and Disengagement, Expectancy–Value Theory, PLS-SEM

INTRODUCTION

In recent years, increasing academic demands, heightened performance expectations, and prolonged exposure to learning stress have drawn scholarly attention to students' psychological well-being, particularly in higher education contexts. Among the growing concerns is learning burnout, a condition characterised by emotional exhaustion and disengagement from academic activities. According to the Job Demands–Resources (JD–R) Model, burnout occurs when academic demands exceed students' available psychological and emotional resources, resulting in energy depletion and motivational withdrawal (Bakker & Demerouti, 2017). In educational settings, exhaustion reflects students' chronic fatigue due to sustained academic pressure, while disengagement represents a loss of interest, reduced involvement, and negative attitudes toward learning.

These burnout experiences are especially critical because they directly interfere with students' ability to sustain motivation, persistence, and engagement in learning tasks.

Student motivation itself is a multidimensional construct that plays a crucial role in academic success. Grounded in Expectancy–Value Theory, motivation is shaped by students' beliefs about their likelihood of success (expectancy), the perceived importance and usefulness of learning tasks (value), and their affective responses such as anxiety or emotional reactions to learning (Wigfield & Eccles, 2000). Empirical studies have consistently shown that students with stronger expectancy beliefs and higher perceived task value demonstrate greater engagement, persistence, and academic achievement (Pintrich & De Groot, 1990). However, motivation does not develop in isolation; it is influenced by learners' emotional states and learning experiences. When students encounter prolonged stress and burnout, their motivational beliefs may gradually deteriorate, leading to reduced learning effectiveness and poorer academic outcomes.

Despite extensive research on motivation and burnout as separate constructs, a clear research gap remains. Existing studies have often examined burnout in relation to factors such as academic self-efficacy, learning engagement, and language learning anxiety (Yang & Zhai, 2022; Zheng et al., 2024), or explored motivation through intrinsic and extrinsic dimensions across demographic variables (Hassan et al., 2021; Truong et al., 2025). Although some studies have acknowledged an inverse relationship between burnout and positive learning outcomes, limited attention has been given to the direct influence of burnout dimensions exhaustion and disengagement on students' motivation as a structured, multidimensional construct. Furthermore, few studies have employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to simultaneously examine these complex relationships within a single integrated framework. Therefore, this study seeks to address this gap by analysing the influence of burnout on students' motivation using PLS-SEM, offering a more comprehensive and theoretically grounded understanding of how burnout shapes motivational processes in academic contexts.

Research Objective, Research Questions, and Hypothesis

The research questions will be answered using SmartPLS analysis using both measurement and structural models.

Table 1 - Research Objective, Research Questions, and Hypothesis

RO	RQ	RESEARCH HYPOTHESIS
To investigate if there is a significant relationship between Exhaustion and Value	Is there a significant relationship between Exhaustion and Value?	Ho1: There is no significant relationship between Exhaustion and Value
To investigate if there is a significant relationship between Exhaustion and Expectancy	Is there a significant relationship between Exhaustion and Expectancy?	Ho2: There is no significant relationship between Exhaustion and Expectancy
To investigate if there is a significant relationship between Exhaustion and Affective	Is there a significant relationship between Exhaustion and Affective?	Ho3: There is no significant relationship between Exhaustion and Affective
To investigate if there is a significant relationship between Disengagement & Value	Is there a significant relationship between Disengagement & Value?	Ho4: There is no significant relationship between Disengagement & Value
To investigate if there is a significant relationship between Disengagement & Expectancy	Is there a significant relationship between Disengagement & Expectancy?	Ho5: There is no significant relationship between Disengagement & Expectancy

To investigate if there is a significant relationship between Disengagement & Affective	Is there a significant relationship between Disengagement & Affective?	Ho6: There is no significant relationship between Disengagement & Affective
To investigate if there is a significant effect between Exhaustion and Motivation	Is there a significant effect between Exhaustion and Motivation?	Ho7: There is no significant relationship between Exhaustion and Motivation
To investigate if there is a significant effect between Disengagement and Motivation	Is there a significant effect between Disengagement and Motivation?	Ho8: There is no significant relationship between Disengagement and Motivation

LITERATURE REVIEW

Theoretical Framework

Two anchor theories are used to support the model suggested in this study. The Expectancy-Value Theory (Wigfield & Eccles, 2000) is used to support the motivational variables or expectancy, value and affective components in the model. The Job Demands-Resources Model (Bakker & Demerouti, 2017) is used to justify the variables for burnout (exhaustion and disengagement).

Motivation Theory

The Expectancy-Value Theory proposed by Wigfield and Eccles (2000) explains that individuals' achievement-related choices, persistence, and performance are mainly determined by two key factors: expectancies for success and subjective task values. *Expectancies for success* refer to a person's belief about how well they will do on an upcoming task, while *subjective task values* refer to how important, useful, interesting, or worthwhile the task is to the individual. Wigfield and Eccles further divided task value into four components: intrinsic value (interest or enjoyment), attainment value (importance of doing well for one's identity), utility value (usefulness for future goals), and cost (perceived negative aspects such as effort, time, or anxiety). According to the theory, people are more likely to engage in, persist at, and perform well in tasks when they believe they can succeed and when they perceive the task as valuable.

Job-Demands-Resources Model and Learning Burnout

The burnout framework proposed by Bakker and Demerouti (2017), often discussed within the Job Demands-Resources Model, explains learning burnout as a condition that arises when academic demands exceed the psychological, emotional, and cognitive resources students possess. In a learning context, exhaustion refers to the feeling of extreme mental and emotional fatigue caused by continuous academic pressure, heavy workloads, or prolonged studying, which reduces students' energy to concentrate, process information, and participate actively in learning tasks. Over time, this persistent exhaustion can lead to disengagement, where students psychologically distance themselves from their studies, lose interest in academic activities, and develop indifferent or negative attitudes toward learning. According to Bakker and Demerouti (2017), exhaustion represents the energy depletion component of burnout, while disengagement represents the motivational withdrawal component, and together they undermine learning effectiveness by lowering students' motivation, persistence, and cognitive engagement with academic tasks.

Past Studies on the Motivation and Burnout

Past Studies on Motivation

Many studies have been done to investigate the motivation of students in learning foreign languages and factors influencing their motivating force. A study by Hassan et al (2021) investigated the difference of motivation in learning French as foreign language across gender. The study focused on exploring motivation in learning French as a foreign language across gender. The authors adopted expectancy theory to investigate the difference of motivation level among 44 male respondents and 126 female respondents. Data from the 170 learners were analysed with SPSS version 26 showed varied gender motivation and perceptions of online language learning. The research concluded that male respondents were motivated by instrumental reasons. Meanwhile, female students were motivated by social reasons such as personal and social needs.

Another study by Truong, Huynh & Ho (2025) also explored motivation in learning foreign languages across gender. The research however focused on extrinsic and intrinsic aspects in evaluating the motivation among students who learn English as foreign language. A total of 320 students took part in this study by answering questionnaires adopted from Gonzales (2010) and Gonzales Lopez (2016). The results generated from the questionnaire showed that students' intrinsic and extrinsic motivation are high. However, students were more extrinsically motivated to learn English as they focus on career, economic enhancement, and communicating with foreigners. Researchers also found that female students are more extrinsically motivated as compared to male students.

Next, a study conducted by Zulkapli et al. (2023) investigated both motivation and demotivation factors related to learning English as a second language. This research had a total of 271 students to partake in this study using a survey adopted by Pintrich & De Groot (1990) for motivation and Campos et al. (2011) for burnout. The researchers found that students’ motivation appeared to be heightened when students channelled their positive emotions and feelings while learning. This also results in decrease of emotional exhaustion. The study concluded that by studying both motivation and demotivation factors in learning foreign language are beneficial for instructors to provide a supportive learning environment that encourages positive emotions, engagement and effective communication.

Overall, past studies explore students’ motivation from multiple aspects of factors including gender differences, intrinsic and extrinsic drivers, and emotional experience during foreign language learning process. This study seeks to examine students’ motivation further by analyzing the influence of burnout on students’ motivation using a PLS-SEM approach. This is to offer a more structured analysis of this relationship.

Past Studies on Burnout

Studies on burnout among foreign language students have been conducted numerous times in the past. A study by Yang & Zhai (2022) examined the relationship between college students’ notion of learning language and foreign language learning burnout. This study utilised a two-part questionnaire to examine students’ conceptions and burnout, with a sample of 363 students from a university in China. The first part of the questionnaire contained 18 items divided by three different sections: Exhaustion, Apathy, and Reduced Self-Efficacy. Meanwhile, the second part consists of 30 items in seven different sections: Testing, Memorizing, Drill and Practice, Grammar, Vocabulary, and Pronunciation, Increasing One’s Knowledge, Application and Communication, Understanding, and Seeing in a New Way. Additionally, the demographic profile of the participants was categorised by gender, major, and year of study. The researchers adopted a five-point Likert scale to measure participants’ responses and found that “testing” was the main factor contributing to burnout among foreign language students. It positively predicted “exhaustion,” “apathy,” and “reduced self-efficacy.” Additionally, “memorising” positively influenced “reduced self-efficacy” but negatively predicted “apathy.” “Language knowledge” was found to negatively predict “exhaustion,” while “understanding and seeing in a new way” negatively predicted “apathy.”

Similarly, another group of researchers investigated burnout among students in China. Cong et al. (2024) explore the relationship between burnout, learning engagement, and academic self-efficacy among learners studying English as a foreign language. This study utilized structural equation modeling (SEM) and path analysis to verify a hypothetical model that includes these variables. A total of 197 Chinese participants comprising undergraduate and postgraduate students participated in this study by answering closed-ended scales questionnaires. The researchers found that learning engagement is positively related with academic self-efficacy. Furthermore, this study also found that students’ burnout exhibits a significant inverse correlation with both factors. The overall analysis of this study indicated that learning engagement acts as an important mediator as it reduces the impact of low academic self-efficacy on student burnout.

Another study by Zheng et al. (2024) examined how burnout among foreign language students is influenced by language learning anxiety, while also exploring the roles of academic peer support and academic self-efficacy in this relationship. This research involved 1,355 college students as participants who learned English as foreign language. These participants took the English Language Learning Anxiety Scale, the English Academic Burnout Scale, Academic Peer Relationship Scale, and the Academic Self-efficacy Scale in order to measure the respective constructs. The researchers found that students' academic burnout was significantly impacted by their language learning anxiety. These two variables were also shown to be mediated by both academic peer support and academic self-efficacy.

Overall, past studies have extensively explored burnout among foreign language students through various factors, including learning approaches, academic self-efficacy, learning engagement, and language learning anxiety. These studies consistently highlight that burnout is closely associated with students' psychological and academic experiences, often demonstrating its negative relationship with positive learning outcomes such as engagement and self-efficacy. However, while prior research has examined burnout alongside several related variables, limited attention has been given to its direct influence on students' motivation. Therefore, this study seeks to extend the existing literature by analysing the influence of burnout on students' motivation using a PLS-SEM approach, offering a more structured and comprehensive understanding of this relationship.

Conceptual Framework and Proposed Model of the Study

The conceptual framework (Figure 1) of this study examines how learning burnout influences students' motivation by integrating constructs from Expectancy–Value Theory and the Job Demands-Resources Model. According to Wigfield and Eccles (2000) students' motivation is shaped by their beliefs about success (expectancy) and the value they attach to learning tasks. These motivational beliefs influence how students approach academic activities, persist in challenging tasks, and regulate their engagement in learning. In this study, students' motivation is operationalized using the instrument developed by Pintrich and De Groot (1990), which measures three key motivational components: value, expectancy, and affective components. The value component refers to students' perceived importance and usefulness of learning tasks, expectancy refers to their beliefs about their ability to succeed academically, and the affective component reflects emotional reactions such as anxiety or emotional responses toward learning. Together, these constructs represent the multidimensional structure of students' academic motivation.

The framework also incorporates learning burnout as a critical factor influencing students' motivational processes. Drawing on the Job Demands-Resources Model proposed by Bakker and Demerouti (2017), burnout occurs when prolonged academic demands exceed the psychological and emotional resources available to students. In educational settings, excessive workloads, performance pressure, and prolonged academic stress may gradually deplete students' energy and motivation. Burnout in this study is conceptualized using the framework developed by Campos et al. (2011), which categorizes burnout into two primary dimensions: exhaustion and disengagement. Exhaustion refers to students' feelings of mental and emotional fatigue resulting from continuous academic demands, while disengagement reflects students' psychological withdrawal, loss of interest, and reduced involvement in academic activities.

Based on the conceptual model presented in Figure 1, the two dimensions of learning burnout which are exhaustion and disengagement, are proposed as exogenous constructs that predict students' motivational orientations. Specifically, exhaustion and disengagement are hypothesised to influence the three motivational components derived from the Expectancy–Value Theory, namely value, expectancy, and affective components. Students experiencing higher levels of burnout are expected to report lower perceptions of task value, weaker expectancy beliefs regarding academic success, and more negative affective responses toward learning. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), this framework evaluates the structural relationships between burnout and motivation, allowing the study to determine the extent to which each burnout dimension explains variations in students' motivational orientations. Overall, the proposed model demonstrates how burnout functions as an important antecedent of motivation among learners of French as a foreign language.

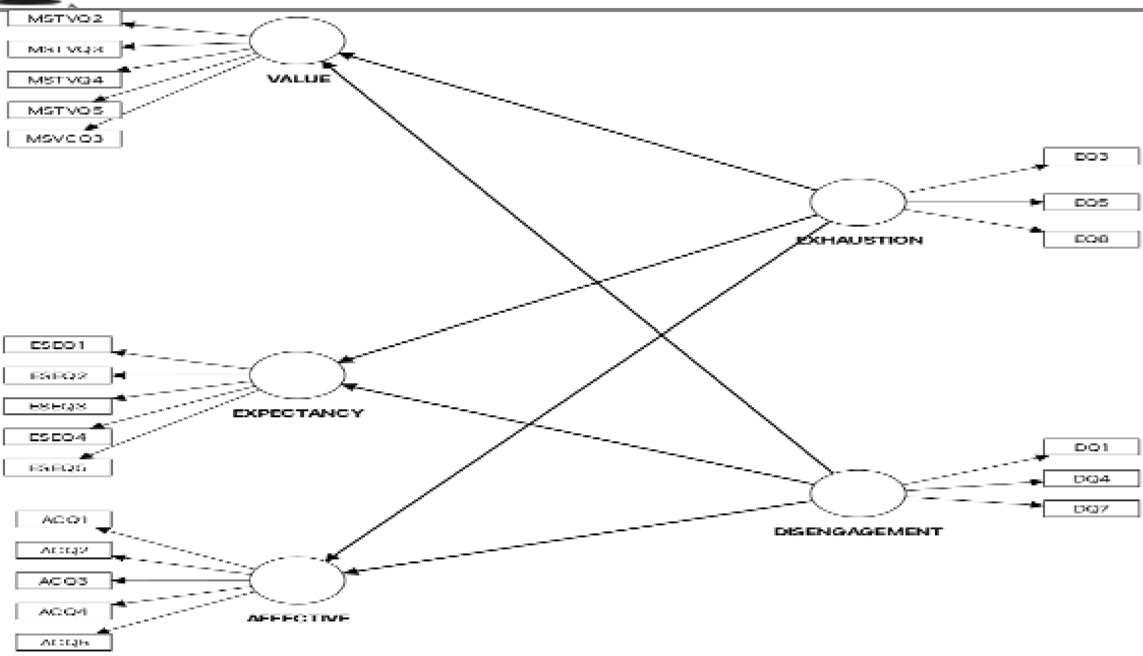

Figure 1- The Conceptual Framework –Influence of Burnout on Learning Motivation

METHODOLOGY

Research Design

This study employs a quantitative design. The research goal is to explore an extension of an existing theory/predict a theory. The model (Figure 1) chosen for this study is a hierarchical component model, Type II, which utilizes a combination of reflective-reflective models. According to Fornell and Bookstein (1982), a reflective model is employed when the construct is a trait and explains the indicators.

Population and Sample

The demographic analysis is presented in percentages. According to Ziegenfuss (2021), researchers report demographic data in percentages to establish sample representatives and allow for generalizability to a larger population. Presenting in percentages also provides an overview of participants' characteristics and offers a clear and understandable picture of the sample makeup.

Table 2- Percentage for Demographic Profile

Question	Demographic Profile	Categories	Percentage (%)
1	Gender	Male (40)	32%
		Female (85)	68%
2	Course	French Level 1(42)	33.6%
		French Level 2 (52)	41.6%
		French Level 3 (31)	24.8%
3	Discipline	Natural Science (83)	66.4%
		Social Science (42)	33.6%

The table presents the demographic profile of respondents based on gender, course , and discipline. In terms of gender, females constitute the majority with 68% (85 respondents), while males account for 32% (40 respondents). For French courses, French Level 2 has the highest proportion at 41.6% (52 respondents), followed by French Level 1 at 33.6% (42 respondents), and French Level 3 at 24.8% (31 respondents). Regarding discipline, most respondents are from Natural Science at 66.4% (83 respondents), whereas Social Science students make up 33.6% (42 respondents).

Instrument

Table 3 presents the distribution of items included in the questionnaire. The instrument used a five-point Likert scale with scale 1 is never. Scale 2 represents rarely. Scale 3 represents sometimes, while scale 4 is often and scale 5 is always.

Table 3- Distribution for Item in Instrument

SECT		CONSTRUCT		VARIABLE	No Of Items	Total Items
B	MOTIVATIONAL SCALE	VALUE COMPONENTS	(i)	Intrinsic Goal Orientation	4	12
			(ii)	Extrinsic Goal Orientation	3	
			(iii	Task Value Beliefs	5	
		EXPECTANCY COMPONENTS	(i)	Students' Perception of Self- Efficacy	5	7
			(ii)	Control Beliefs for Learning	2	
		AFFECTIVE COMPONENTS				5
C	BURNOUT	BURNOUT- EXHAUSTION				8
		BURNOUT- DISENGAGEMENT				8
		TOTAL NO OF ITEMS				40

The questionnaire, adapted from Campos et al. 2011 and Pintrich & DeGroot, 1990 comprises variables representing the model formed. The questionnaire consisted of two established instruments adapted for the present study. Students' motivational orientations were measured using the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich and De Groot (1990). The instrument comprised three motivational constructs: Value Components (intrinsic goal orientation, extrinsic goal orientation, and task value beliefs), Expectancy Components (students' self-efficacy and control beliefs for learning), and the Affective Component, which measures students' anxiety and emotional reactions towards learning. Learning burnout was measured using the Burnout Scale developed by Campos et al. (2011), consisting of two dimensions: Exhaustion, which reflects emotional and mental fatigue resulting from academic demands, and Disengagement, which represents students' psychological withdrawal and reduced interest in learning activities. All items were measured using a five-point Likert scale ranging from 1 (Never) to 5 (Always).

Data Collection and Data Analysis

Data is collected via a Google Form. The data is then analyzed using SmartPLS 4 through two main stages. As suggested by Hair et al. (2017), data analysis is done at two levels: the measurement and structural model. The first stage is the measurement model, which measures the outer model. The second stage is the structural model, which measures the inner model. The analyzed data is used to answer the research questions and also to confirm the model chosen.

FINDINGS AND DISCUSSION

The model formed for this study is that of lower order construct (LOC). The reflective measurement model was chosen. A reflective measurement model is the formation of a single unobserved latent construct and this construct influences multiple variables (indicators). Another key feature of LOC is that the indicators are interchangeable. In this study, the construct Value Components, Expectancy Components, Affective Components, Burnout-Exhaustion and Burnout-Disengagement.

The findings are presented in two stages. The first stage presents the measurement model, and the second stage reveals the structural model as well as answers research questions.

Measurement Model

In SmartPLS, the measurement model assesses the reliability and validity of the constructs. This is done by examining the relationships between them and their observable behavior. The measurement model measures the outer model. Figure 2 below shows the measurement model for this study. Further detailed explanation of this model is elaborated in tables below.

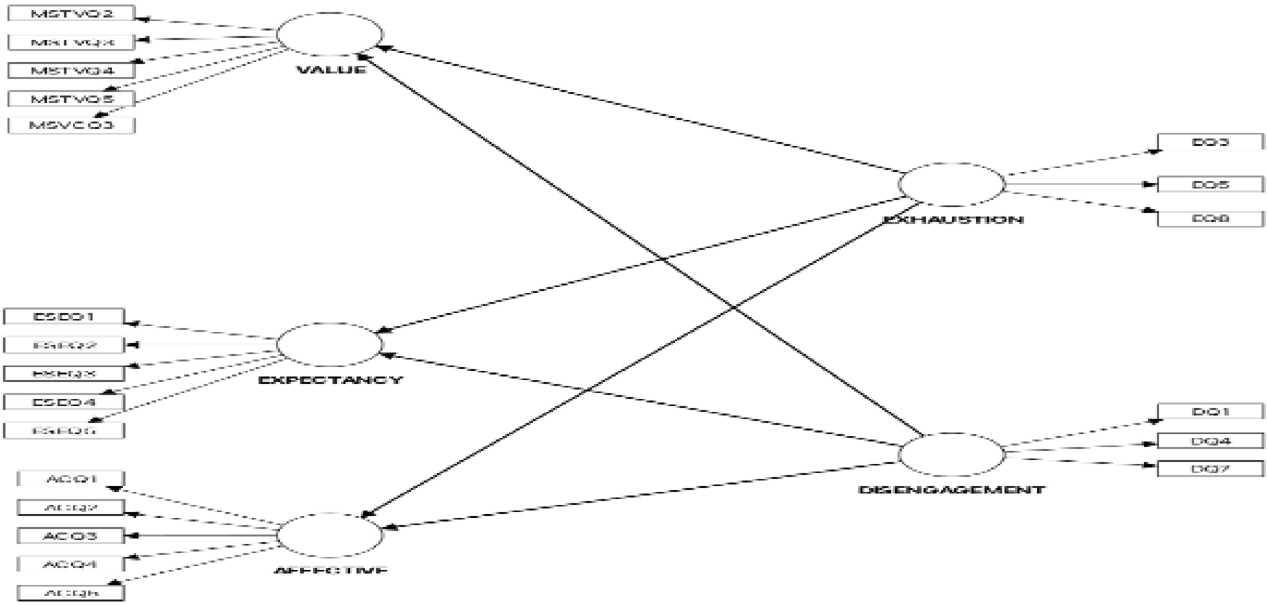

Figure 2- Measurement Model

Reliability

According to Ringle & Sarstedt (2016), reliability is assessed by checking indicator reliability and internal consistency reliability. Internal consistency is done using Composite reliability (rho_c) and Cronbach's Alpha. The cut-off value for Cronbach's Alpha is 0.70 to 0.90. The cut-off values for composite reliability (rho_c) are 0.70-0.90. For indicator reliability, the factor loadings cut-off values are >0.70 and squared loadings ≥0.50. Finally, the cut-off values for Average Variance Extracted (AVE) ≥0.50.

Prior to the assessment of construct reliability and validity, indicator reliability was examined using outer loadings in SmartPLS. Following the recommendation of Hair et al. (2017), indicators with loadings below the recommended threshold of 0.70 were removed to improve construct reliability and convergent validity. Consequently, five Exhaustion items and five Disengagement items were excluded from the final measurement model, leaving three indicators for each burnout construct. Only the retained indicators are presented in Tables 4 and 5.

Table 4 -Results for Reliability- Exhaustion

CONSTRUCT / ITEM	FACTOR LOADING	CRONBACH'S ALPHA	COMPOSITE RELIABILITY (rho_c)	AVERAGE VARIANCE EXTRACTED (AVE)
		0.741	0.848	0.652
EQ3	0.83			
EQ5	0.719			
EQ8	0.867			

Table 4 presents the reliability and validity results for the construct Exhaustion. The factor loadings for the items range from 0.719 to 0.867, indicating that all items adequately represent the construct. Specifically, item EQ8 shows the highest loading (0.867), followed by EQ3 (0.83) and EQ5 (0.719). The construct demonstrates good internal consistency, with a Cronbach's alpha of 0.741 and a composite reliability (ρc) of 0.848, both exceeding commonly accepted thresholds. Additionally, the average variance extracted (AVE) of 0.652 suggests that the construct explains a satisfactory proportion of variance among its indicators, confirming acceptable convergent validity.

Table 5 -Results for Reliability- Disengagement

CONSTRUCT/ ITEM	FACTOR LOADING	CRONBACH'S ALPHA	COMPOSITE RELIABILITY (rho_c)	AVERAGE VARIANCE EXTRACTED (AVE
		0.706	0.836	0.63
DQ1	0.815			
DQ4	0.78			
DQ7	0.784			

Table 5 presents the reliability and validity results for the disengagement construct. The factor loadings for the three items are DQ1 (0.815), DQ4 (0.780), and DQ7 (0.784). The three items are all above the recommended threshold, indicating strong item reliability. The construct demonstrates acceptable internal consistency with a Cronbach's alpha of 0.706. Additionally, the composite reliability (rho_c) is 0.836, exceeding the suggested minimum, which further supports reliability. The average variance extracted (AVE) value of 0.63 indicates good convergent validity, as it surpasses the 0.50 benchmark. Overall, the results confirm that the disengagement construct is both reliable and valid.

Table 6 -Results for Reliability- Value Components

CONSTRUCT /ITEM	FACTOR LOADING	CRONBACH'S ALPHA	COMPOSITE RELIABILITY (rho_c)	AVERAGE VARIANCE EXTRACTED (AVE
		0.893	0.922	0.702

MSTVQ2	0.851	
MSTVQ3	0.836	
MSTVQ4	0.846	
MSTVQ5	0.878	
MSVCQ3	0.775	

Table 6 presents the reliability and validity results for the value components construct. The factor loadings for all items are robust: MSTVQ2 (0.851), MSTVQ3 (0.836), MSTVQ4 (0.846), MSTVQ5 (0.878), and MSVCQ3 (0.775). All items are high and exceed the acceptable threshold, indicating strong item reliability. The construct demonstrates excellent internal consistency, with a Cronbach's alpha of 0.893. Additionally, the composite reliability (rho_c) is 0.922, further confirming high reliability. The average variance extracted (AVE) value of 0.702 exceeds the recommended level, indicating good convergent validity. Overall, the value components constructed are both highly reliable and valid.

Table 7 -Results for Reliability- Expectancy Components

CONSTRUCT/ITEM	FACTOR LOADING	CRONBACH'S ALPHA	COMPOSITE RELIABILITY (rho_c)	AVERAGE VARIANCE EXTRACTED (AVE
		0.918	0.938	0.754
ESEQ1	0.852			
ESEQ2	0.8			
ESEQ3	0.926			
ESEQ4	0.913			
ESEQ5	0.844			

Table 7 presents the reliability and validity results for the expectancy components constructed. All items ESEQ1 (0.852), ESEQ2 (0.800), ESEQ3 (0.926), ESEQ4 (0.913), and ESEQ5 (0.844) show strong factor loadings above the acceptable threshold, indicating good item reliability. The construct demonstrates excellent internal consistency with a Cronbach's alpha of 0.918. Additionally, the composite reliability (rho_c) is 0.938, further confirming high reliability. The average variance extracted (AVE) value of 0.754 exceeds the recommended level, indicating strong convergent validity. Overall, the expectancy components constructed are highly reliable and valid.

Table 8 -Results for Reliability- Affective Components

CONSTRUCT /ITEM	FACTOR LOADING	CRONBACH'S ALPHA	COMPOSITE RELIABILITY (rho_c)	AVERAGE VARIANCE EXTRACTED (AVE
		0.901	0.926	0.716
ACQ1	0.87			
ACQ2	0.815			

ACQ3	0.779	
ACQ4	0.859	
ACQ5	0.855	

Table 8 presents the reliability and validity results for the affective components construct. The five items ACQ1 to ACQ5 demonstrate strong factor loadings above the acceptable threshold, indicating good item reliability.

The construct shows excellent internal consistency, with a Cronbach's alpha of 0.901. Furthermore, the composite reliability (rho_c) is 0.926, supporting high reliability. The average variance extracted (AVE) value of 0.716 exceeds the recommended level, indicating strong convergent validity. Overall, the affective components constructed are both highly reliable and valid.

Validity

According to Ramayah et.al. (2018), for validity, the Discriminant validity (HTMT) needs to be <0.85 or <0.90.

Table 9- Discriminant Validity (HTMT)

	AFFECTIVE	**DISENGAGEMENT**	**EXHAUSTION**	**EXPECTANCY**
AFFECTIVE				
DISENGAGEMENT	0.489			
EXHAUSTION	0.432	0.775		
EXPECTANCY	0.44	0.817	0.731	
VALUE	0.318	0.716	0.537	0.76

Table 9 presents the discriminant validity results using the HTMT. The HTMT analysis further confirms that all construct pairs demonstrate satisfactory discriminant validity, as all values remain below the recommended threshold of 0.90.

The highest HTMT value is observed between expectancy and disengagement (0.817), followed by exhaustion and disengagement (0.775), and value and expectancy (0.760). Moderate relationships are also found between expectancy and exhaustion (0.731) as well as value and disengagement (0.716). Meanwhile, lower HTMT values are evident between value and affective (0.318), exhaustion and affective (0.432), and expectancy and affective (0.440). These results reinforce that each construct is empirically distinct and captures different underlying dimensions within the model.

Structural Model

In SmartPLS, the structural model visualizes the hypothesized causal relationships between constructs. The structural model is thus formed after the researcher has established the reliability and validity in the measurement model. For the analysis of the structural model, the researcher runs bootstrapping and examines the collinearity, path coefficients of determination, effect size, PLS predict, and IPMA. In addition to that, the analysis in the structural model allows the researcher to answer research questions 1-6 and hypotheses 1-3). Figure 3 below shows the structural model for this study. Detailed explanation is elaborated in Tables below.

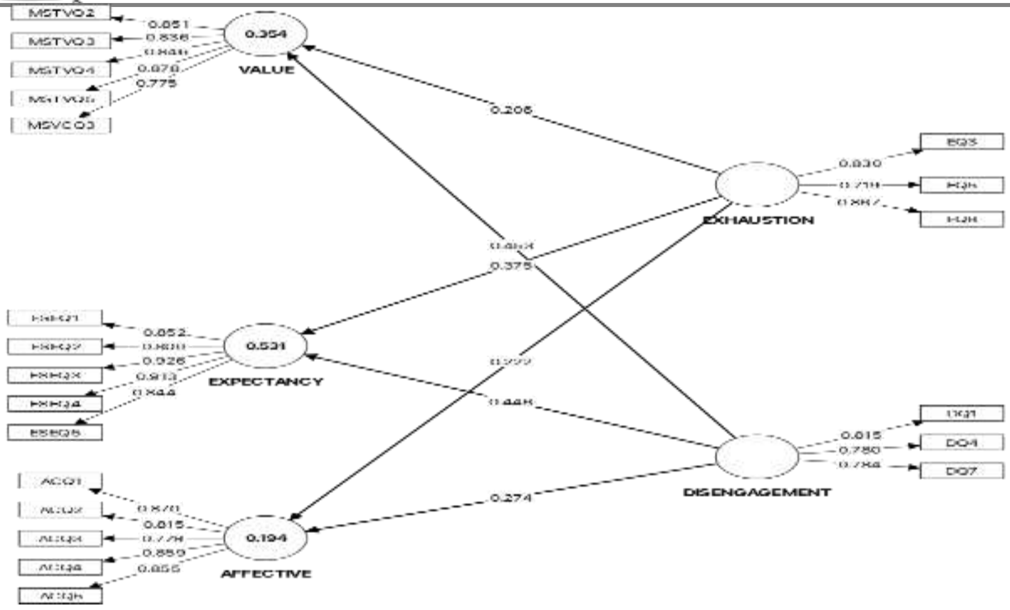

Figure 3. Structural Model Integrating the Expectancy–Value Theory and the Job Demands–Resources (JD-R) Model Collinearity

According to Ringle & Sarstedt (2016), the cut-off value for collinearity inner model VIF is ≤ 5.0.

Table 10- Collinearity

	Original sample (O)
DISENGAGEMENT -> AFFECTIVE	1.483
DISENGAGEMENT -> EXPECTANCY	1.483
DISENGAGEMENT -> VALUE	1.483
EXHAUSTION -> AFFECTIVE	1.483
EXHAUSTION -> EXPECTANCY	1.483
EXHAUSTION -> VALUE	1.483

Table 10 presents the collinearity assessment results for the structural model using the original sample values. All predictor relationships specifically from disengagement to affective, expectancy, and value, as well as exhaustion to affective, expectancy, and value, show identical values of 1.483. These values are well below the commonly accepted threshold of 5.0 (or more conservatively 3.3), indicating no issues of multicollinearity among the constructs. This suggests that the independent variables do not exhibit high intercorrelations and can reliably explain the dependent constructs without redundancy. Overall, the model demonstrates acceptable collinearity levels.

Coefficients of determination (R^2)

According to Ramayah,et.al. (2018) For coefficients of determination (R^2) 0.2 to 0.7, depending on the field of study. Social Sciences & Economics follows the range above.

Table 11- R^2

	Original sample (O)
AFFECTIVE	0.194
EXPECTANCY	0.531
VALUE	0.354

Table 11 shows the coefficient of determination (R^2) values for the endogenous constructs in the model. The results show that expectancy has the highest explanatory power with an R^2 value of 0.531, indicating that 53.1% of its variance is explained by the predictor variables. Value demonstrates a moderate level of explanatory power with an R^2 of 0.354, while affective shows a lower explanatory level with an R^2 of 0.194. These findings suggest that the model has strong predictive relevance for expectancy, moderate for value, and relatively weak for affective.

P-Value

Table 12- Interpretation for p-value

Thresholds	Interpretation	Decision
$p \leq 0.05$	Often considered statistically significant	Reject H_0
$p \leq 0.01$	Indicates very strong evidence against H_0	Reject H_0
$p > 0.05$	Weak or no evidence against H_0	Failure to reject H_0

According to Goodman (1999), the p-value threshold is the cut-off for determining statistical significance, most commonly set at 0.05. Below is the table that interprets the threshold.

Table 12 shows the interpretation for p-value. According to Goodman (1999), if the p-value is $p \leq 0.05$, the data is often considered statistically significant and the null hypothesis is rejected. If it is $p \leq 0.01$, then it indicates very strong evidence to reject the null hypothesis (H_0). However, a $p > 0.05$ is considered weak and there is no evidence to reject the null hypothesis.

Table 13-Path Coefficient for the current study

	T statistics (|O/STDEV|)	P values
DISENGAGEMENT -> AFFECTIVE	2.668	0.008
DISENGAGEMENT -> EXPECTANCY	5.436	0
DISENGAGEMENT -> VALUE	4.798	0
EXHAUSTION -> AFFECTIVE	1.776	0.076
EXHAUSTION -> EXPECTANCY	4.333	0
EXHAUSTION -> VALUE	1.923	0.054

Table 13 presents the path coefficients for the current study, including T statistics and p-values. Disengagement shows significant positive effects on affective (T = 2.668, p = 0.008), expectancy (T = 5.436, p

< 0.001), and value (T = 4.798, $p < 0.001$). Similarly, exhaustion has a significant effect on expectancy (T = 4.333, $p < 0.001$). However, exhaustion does not significantly influence affective (T = 1.776, p = 0.076) and value (T = 1.923, p = 0.054), as their p-values exceed the 0.05 threshold. Overall, the results indicate that disengagement is a stronger predictor compared to exhaustion.

Effect Size (f^2)

The effect size (f^2) analysis was conducted to determine the magnitude of the influence exerted by each predictor construct on the endogenous variables. According to Ramayah et al. (2018), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The results reveal that disengagement exerts a medium effect on expectancy ($f^2 = 0.286$) and value ($f^2 = 0.214$), while its influence on affective components is small ($f^2 = 0.063$). In contrast, exhaustion demonstrates a medium effect only on expectancy ($f^2 = 0.203$). Its effects on value ($f^2 = 0.044$) and affective components ($f^2 = 0.041$) are negligible, consistent with the non-significant path coefficients reported earlier. These findings further support the conclusion that disengagement is a stronger predictor of students' motivational orientations than exhaustion.

According to Ringle et al. (2024) for effect size, values from 0.02 to 0.15 are considered small. Values between 0.15 to 0.35 are considered medium while values 0.35 and above are considered large.

Table 14- Effect Size

	Original sample (O)	**Interpretation**
DISENGAGEMENT -> AFFECTIVE	0.063	Small effect
DISENGAGEMENT -> EXPECTANCY	0.286	Medium effect
DISENGAGEMENT -> VALUE	0.214	Medium effect
EXHAUSTION -> AFFECTIVE	0.041	No meaningful effect
EXHAUSTION -> EXPECTANCY	0.203	Medium effect
EXHAUSTION -> VALUE	0.044	No meaningful effect

Table 14 presents the effect size (f^2) of relationships between disengagement, exhaustion, and the outcome variables. Disengagement shows a small effect on affective (0.063) and medium effects on expectancy (0.286) and value (0.214), indicating a stronger influence on the latter two. For exhaustion, the effect on affective (0.041) and value (0.044) is minimal and interpreted as no effect, while a medium effect is observed on expectancy (0.203). Overall, the results suggest that disengagement has more meaningful and consistent impacts across variables, whereas exhaustion demonstrates limited influence except for its moderate effect on expectancy.

PLS Predict (Q^2)

In PLS-SEM, it is stated that $Q^2 \geq 0$ (Ringle et.al., 2024). Table 15 below reveals the PLS Predict (Q^2) for the dependent variable. The analysis reveals the Q^2 for all items in the dependent variable.

Table 15- PLS Predict (Q^2)

	Q²predict	**RMSE**	**MAE**
AFFECTIVE	0.15	0.934	0.736
EXPECTANCY	0.508	0.716	0.55

VALUE	0.309	0.859	0.654

The PLS Predict analysis was conducted to evaluate the model's out-of-sample predictive capability for the three endogenous constructs: value, expectancy, and affective components. Since all Q^2predict values are greater than zero (Affective = 0.150; Expectancy = 0.508; Value = 0.309), the structural model demonstrates predictive relevance. Among the three constructs, expectancy exhibits the strongest predictive relevance, followed by value and affective components. These findings indicate that the proposed PLS-SEM model possesses acceptable predictive capability for explaining students' motivational orientations.

IPMA

According to Ringle & Sarstedt (2016), IPMA is used to evaluate the performance and importance of the chosen constructs or indicators within a model. In the context of this study, individual IPMA analysis was done on each construct and reported in Table 16.

Table 16- Latent Variables Average Performance (Performance)

	LV performance value, average
AFFECTIVE	52.275
DISENGAGEMENT	69.995
EXHAUSTION	67.237
EXPECTANCY	67.819
VALUE	77.721

Table 16 presents the average performance scores of the latent variables on a rescaled scale ranging from 0 to 100. Among the five constructs, Value recorded the highest performance score (77.721), indicating that students generally perceived learning French as meaningful and worthwhile. This was followed by Disengagement (69.995), Expectancy (67.819), and Exhaustion (67.237), which demonstrated moderate performance levels. In contrast, the Affective component recorded the lowest performance score (52.275), suggesting that students experienced comparatively lower positive emotional responses towards learning French.

The performance scores provide a descriptive overview of the relative standing of each construct in the proposed model. Although IPMA is typically interpreted using both performance scores and importance (total effects), only the performance values are reported in the present study. Therefore, the interpretation is limited to describing the relative performance of the constructs based on the available results.

CONCLUSION

Summary of Findings and Discussion

Table 17- Outcome of Research Hypothesis

NO	Research Question	Research Hypothesis	Outcome
1	Is there a significant relationship between Exhaustion and Value?	Ho1: There is no significant relationship between Exhaustion and Value	Accept null hypothesis There is no significant relationship between Exhaustion and Value.
2	Is there a significant	Ho2: There is no significant	Reject null hypothesis

	relationship between Exhaustion and Expectancy?	relationship between Exhaustion and Expectancy	There is a significant relationship between Exhaustion and Expectancy.
3	Is there a significant relationship between Exhaustion and Affective?	Ho3: There is no significant relationship between Exhaustion and Affective	Accept null hypothesis There is no significant relationship between Exhaustion and Affective.
4	Is there a significant relationship between Disengagement & Value?	Ho4: There is no significant relationship between Disengagement and Value	Reject null hypothesis There is a significant relationship between Disengagement and Value.
5	Is there a significant relationship between Disengagement & Expectancy?	Ho5: There is no significant relationship between Disengagement and Expectancy	Reject null hypothesis There is a significant relationship between Disengagement and Expectancy.
6	Is there a significant relationship between Disengagement & Affective?	Ho6: There is no significant relationship between Disengagement and Affective	Reject null hypothesis There is a significant relationship between Disengagement and Affective.
7	Is there a significant effect between Exhaustion and Motivation?	Ho7: There is no significant relationship between Exhaustion and Motivation	Reject null hypothesis There is a significant effect between Exhaustion and Motivation.
8	Is there an effect significant between Disengagement and Motivation	Ho8: There is no significant relationship between Disengagement and Motivation	Reject null hypothesis There is a significant effect between Disengagement and Motivation.

Table 17 summarizes the outcomes of eight research hypotheses examining relationships between exhaustion, disengagement, and other variables. The results show that the null hypothesis is accepted for the relationships between exhaustion and value, and exhaustion and affective, indicating no significant relationships. However, the null hypothesis is rejected for all other hypotheses, including relationships between exhaustion and expectancy, as well as disengagement with value, expectancy, and affective, demonstrating significant relationships. Additionally, both exhaustion and disengagement have significant effects on motivation. Overall, the findings highlight that disengagement is consistently significant, while exhaustion shows mixed results.

This study set out to examine the influence of students' burnout on their motivation by integrating the Expectancy–Value Theory and the Job Demands–Resources Model and testing the proposed relationships using PLS-SEM. Overall, the findings reveal that burnout significantly shapes key dimensions of student motivation, though its effects vary across components. Specifically, disengagement emerged as a strong and consistent predictor of motivational outcomes, showing significant relationships with value, expectancy, and affective components. In contrast, exhaustion demonstrated a more selective influence, significantly affecting expectancy but not value or affective components. These results suggest that motivational withdrawal (disengagement) may be more detrimental to students' motivation than mere emotional or physical fatigue, supporting previous arguments that disengagement represents the motivational core of burnout (Bakker & Demerouti, 2017). Aligned with Expectancy–Value Theory, students who experience disengagement tend to report lower beliefs in their ability to succeed and reduced perceptions of task importance, which ultimately undermines their overall motivation (Wigfield & Eccles, 2000).

Implications and Suggestions for Future Research

Figure 4 below presents the proposed model for the influence of burnout on learners' motivation. This study has shown that exhaustion has a significant effect on expectancy. The study also reveals that disengagement has effects on value, expectancy, and affective components.

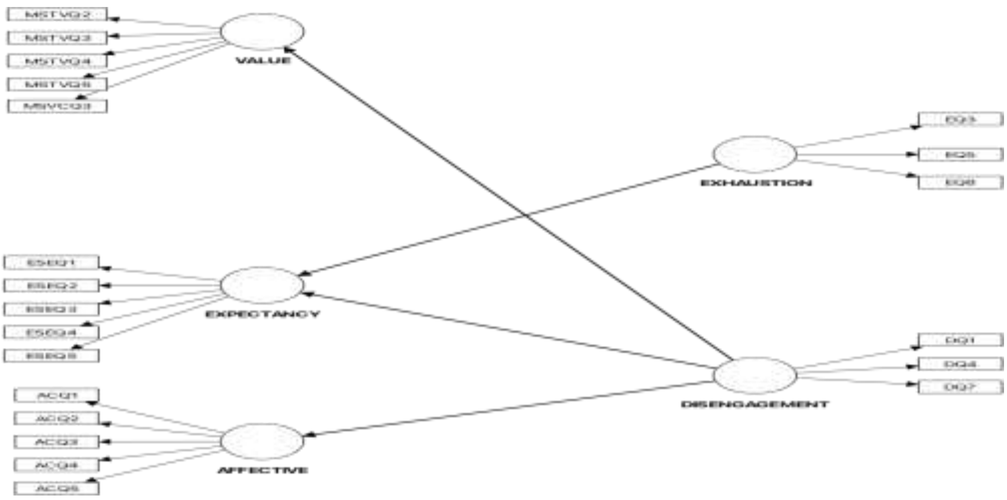

Figure 4- The Proposed Model

The implications of these findings are both theoretical and practical. Theoretically, this study contributes to the existing literature by empirically linking burnout dimensions directly to motivation within a unified PLS-SEM framework, addressing a gap noted in prior research that often examined these constructs separately. By confirming the robustness of the measurement and structural models, the study also supports the use of validated instruments developed by Pintrich and De Groot (1990) and Campos et al. (2011) in the context of higher education. Practically, the results highlight the importance of addressing student disengagement in academic settings. Educators and institutions should focus on reducing psychological withdrawal by fostering meaningful learning activities, enhancing student engagement, and providing adequate academic and emotional support. Such strategies may help buffer the negative effects of burnout and sustain students' expectancy beliefs and perceived task value (Zolkapli et al., 2023).

Despite its contributions, this study is not without limitations, which point to directions for future research. Future studies could adopt a longitudinal design to better capture the dynamic relationship between burnout and motivation over time. In addition, expanding the sample across different institutions, disciplines, or cultural contexts may enhance generalizability. Researchers may also consider incorporating mediating or moderating variables such as academic self-efficacy, peer support, or learning engagement to further enrich the model (Cong et al., 2024). Collectively, these future efforts can deepen understanding of how burnout develops and how motivation can be effectively sustained in demanding academic environments.

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