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Assessing the Micro-Level Outcomes of Higher Education Governance: How the EMI Transition and AI Adoption Shape Students' Self-Perceived Employability at the University of Algiers 3

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Abstract:

This study investigates the micro-level operational outcomes of higher education governance reforms in Algeria. Specifically, it examines how the transition to English Medium Instruction (EMI) and the concurrent rise of Artificial Intelligence (AI) shape students' Self-Perceived Employability (SPE), a subjective psychological self-assessment rather than actual job hiring rates within a pioneer Bachelor Business Administration cohort.

The results reveal that while English Self-Efficacy enhances SPE, Cognitive Load has a negative impact. As for AI dependency, it acts as a positive driver of SPE, serving as a coping mechanism to mitigate linguistic and academic challenges rather than being a sign of academic failure.

Keywords: Higher Education Governance; English Medium Instruction; AI Dependency; Self-Perceived Employability; PLS-SEM.

Jel Classification Codes: I23, I28, O33

1. INTRODUCTION

Over the past two decades, the Ministry of Higher Education and Scientific Research (MESRS) has implemented several strategies to align Algerian higher education with international standards. This implementation process reflects a continuous evolution: it began with the adoption of the LMD reform and the institutionalization of quality assurance frameworks and continued with a digital transformation strategy through the deployment of online platforms to modernize university governance and instruction. As a continuation of these foundational strategies, the MESRS required universities to establish monitoring committees, to inventory available language skills, and to deploy intensive training programs to gradually introduce English as a Medium of Instruction (EMI) for the 2023–2024 academic year (MESRS, 2023).

The main objective of this public governance policy is to modernize academic programs, following the example of many non-English-speaking countries such as Taiwan, China, Kazakhstan, and several European nations, which have opted to adopt the English language to increase the visibility of their research and the employability of their graduates (Macaro & al., 2018).

Alongside the EMI transition, Algerian universities, much like foreign institutions, must navigate governance challenges through the rise of Artificial Intelligence (AI). AI tools are now an integral part of academic circles. This is prompting universities to find governance mechanisms to regulate its use, whether it’s related to academic assessment or even teaching and research practices.

At the international level, although various institutions have attempted to address this rapid growth, institutional governance responses remain too fragmented in the face of the digital skills gap (Valentini & Blancas, 2025). In Algeria, efforts to manage this rapid development in the use and application of AI have taken the form of targeted public governance initiatives. Digitization plans and strategies for integrating AI have been enacted by the MESRS, including the establishment of "House of Artificial Intelligence" within all higher education institutions.

At the institutional level, the University of Algiers 3 implemented these governance reforms through the official launch of the EMI program for the 2023-2024 academic year proposed only for students wishing to pursue this path. This transition culminated in July 2026 with the graduation of the first cohort of bachelor's degree (L3) students who received their instruction entirely in English throughout their undergraduate studies. In parallel, the university established the "House of Artificial Intelligence", which was officially inaugurated on January 28, 2025.

1.1 Research Problem and Question

This research attempts to answer the following central question: *"To what extent do the micro-level outcomes of higher education governance, manifested through English Self-Efficacy, Cognitive Load, and AI Dependency, shape students' Self-Perceived Employability under the shifting EMI landscape and rising technological reliance at the University of Algiers 3?"*

This study addresses the following sub-question as well: *"How do institutional governance structures and policy implementation frameworks influence and shape these relational dynamics among students?"*

1.2 Objectives of the Study

Our research problem has objectives closely tied to institutional governance, namely:

- ✓ To evaluate the direct impact of English Self-Efficacy (ESE), Cognitive Load (CL), and AI Dependency (AID) on students' Self-Perceived Employability (SPE) to provide quantifiable performance indicators for university governance.
- ✓ To analyze whether Cognitive Load (CL) directly drives students toward AI Dependency (AID) as a coping mechanism.
- ✓ To evaluate the direct impact of English Self-Efficacy (ESE) on AI Dependency (AID).

1.3 Hypothesis development

- ✓ **Main Hypothesis**

H_M: The micro-level outcomes of higher education governance show a structural tension, in which English Self-Efficacy (ESE) directly enhances

Self-Perceived Employability (SPE), whereas resulting Cognitive Load (CL) and AI Dependency (AID) act as behavioral constraints on this readiness.

✓ **Sub-Hypotheses**

H_1: English Self-Efficacy (ESE) has a significant positive direct effect on Self-Perceived Employability (SPE).

H_2: Cognitive Load (CL) has a significant negative direct effect on Self-Perceived Employability (SPE).

H_3: AI Dependency (AID) has a significant negative direct effect on Self-Perceived Employability (SPE).

H_4: Cognitive Load (CL) has a significant positive direct effect on AI Dependency (AID).

H_5: English Self-Efficacy (ESE) has a significant negative direct effect on AI Dependency (AID).

1.4 Significance of the Study

This study is important for four main reasons:

- ✓ It constitutes a continuation of public and organizational governance theories in the academic field, as it evaluates how strategic management handles new technologies (AI) alongside linguistic changes (EMI).
- ✓ By applying a structural equation modelling approach (PLS-SEM) to a real-world pioneering cohort (graduating in July 2026), this study provides quantifiable indicators of governance performance rather than just simple conceptual assumptions.
- ✓ It offers the Ministry (MESRS) and the leadership teams of the University of Algiers 3 a micro-level audit of the 2023 reforms. Although the empirical data is limited to a single pioneer cohort, these early feedback indicators can help them adjust future AI and language policies.
- ✓ It addresses long-term socio-economic impacts by offering policy insights to enhance graduate employability in multinational markets and align higher education outputs with national economic modernization goals.

1.5 Design and Approach of the study

This study adopts a quantitative deductive approach. As for the statistical method, we used Partial Least Squares Structural Equation Modelling (PLS-SEM) executed via SmartPLS 4 due to the predictive

nature of our structural framework.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Governance of Higher Education and Implementation of Public Policies

In response to globalization, the conceptualization of higher education governance was marked by a paradigm shift. Historically, it was initially understood through traditional bureaucratic or collegial models, in which the State exercised direct administrative control over the institutions (Baldridge, 1971). However, universities around the world have turned toward the principles of New Public Management (NPM). Thus, this managerial shift has redefined universities not as state-funded administrative units, but as autonomous, entrepreneurial, and proactive organizational entities (Clark , 1998).

In this context, modern governance defines universities as strategic actors whose main function is to drive change. However, the translation of a political vision into academic reality is not a linear process where directives are perfectly translated into the expected outputs. The traditional framework posits that the success of a public policy fundamentally depends on the clarity of its statutory objectives, the adequacy of the allocated resources, and the strict adherence to guidelines by the implementation officials (Sabatier & Mazmanian, 1980). However, the complex and loosely coupled nature of higher education systems (Weick, 1976) creates a persistent policy-implementation gap between macro-level strategic visions and micro-level operational realities (Gornitzka & al., 2005).

In this perspective, higher education institutions act as critical actors at the meso-level. In fact, they serve as an organizational interface translating abstract political strategies into operational and actionable indicators. The University of Algiers 3 perfectly embodies this role following the recent directives issued by the MESRS. While the macro-level government directive was clear, it was up to the meso-level leaders to operationalize these objectives through the concrete creation of monitoring committees, the deployment of local language training programs, and the development of specialized digital spaces such as the "House of Artificial

Intelligence".

Finally, the university campus becomes the ground where the actual performance of public governance is tested and measured. That is why the success of a political reform must be evaluated at the point of terminal impact, at the micro level, where macro decisions translate into skills, constraints, and behaviors among students.

2.2 The Shift toward English-Medium Instruction (EMI)

English Medium Instruction (EMI) is defined as: *"The use of the English language to teach academic subjects (other than English itself) in countries or jurisdictions where the first language of the majority of the population is not English."* (Macaro & al., 2018, p. 37).

In line with this definition, educational systems and governments worldwide have rapidly adopted EMI as part of their national higher education modernization agendas (Galloway & Rose, 2021). At the macro-institutional level, policymakers implement EMI because for them total linguistic exposure will tend to improve students' skills, to shape a competitive English-speaking workforce (Galloway & Rose, 2021).

Dearden (2014) highlights in a global baseline study that while the implementation of EMI is rapid and heavily dictated by top-down executive decisions across the world, this phenomenon provides almost no empirical validation as to its real consequences on the ground, at the micro level, thus, according to the author, the implementation of EMI is too often fast-tracked by policymakers who associate it with economic growth and professional prestige (Dearden, 2014). However, she demonstrates that the euphemistic nature of public policies often hides practical operational challenges as well as the controversial impact on academic depth. This prompts researchers to go beyond official discourses to assess how these policies shape students' concrete reality (Dearden, 2014).

Apprehending how students experience and navigate EMI at the micro-level requires exploring the psychological factors shaping their academic behaviors. In this study, this individual dimension is examined by drawing on Bandura's (1997) Social Cognitive Theory, and more particularly through the central concept of self-efficacy. Bandura (1997) defines self-efficacy as *"beliefs in one's capabilities to organize and execute the courses of action*

required to produce given attainments." (Bandura, 1997, p. 3). Within an EMI context, students' beliefs regarding their cognitive and linguistic capabilities influence their academic adaptation, motivation, and resilience when they come across complex scientific content delivered in a foreign language. In Algeria, this transition occurs within a unique tripartite linguistic reality (Arabic, French, and English), where the professional dominance of French increases daily translation efforts for students.

2.3 Student AI Adoption and Dependency in EMI Contexts

In response to the pressures of top-down macro-educational reforms, students adopt autonomous coping strategies to mitigate the implementation gaps that appear on the ground. According to the transactional theory of stress and coping, when individuals encounter environmental demands that exceed their available resources, they deploy cognitive and behavioral coping strategies to manage the situation (Lazarus & Folkman, 1984). In the university context, generative AI is thus mobilized as an immediate resource to mitigate the impact of these macro-level directives.

However, this reactive coping mechanism does not remain a simple temporary expedient; through a continuous process of motivational internalization, it evolves into a structured practice. Grounded in self-determination theory, Yin et al. (2026) demonstrate that students' AI dependency is significantly driven by their underlying motivational regulations. Specifically, through *"identified regulation"*, students perceive generative AI as a valuable and functional tool for their academic growth rather than a constraint (Yin & al., 2026).

Within this EMI framework, this technological adoption directly determines micro-outcomes. When navigating EMI challenges, students systematically rely on AI tools to address skills lacking. What began as a temporary coping strategy becomes normalized. Through this sustained identified regulation, their usage eventually shifts toward a state of functional integration, characterized by what Yang and al.'s (2025) concept defines as tool dependence, where AI offers functional support while students still reason independently, rather than cognitive dependence, where AI replaces entirely the student's thinking and judgment (Yang & al., 2025). Within this dynamic, English proficiency was found to significantly predict EFL students' digital

literacy self-efficacy (Alsmari, 2021). Although her study did not address generative AI specifically, this logic extends naturally to prompt design because it requires similar linguistic precision and clarity (Alsmari, 2021).

2.4 Cognitive Load Theory as an Explanatory Mechanism

Cognitive load theory posits that the limited processing capacity of short-term memory hinders schema acquisition when individuals face complex problem-solving tasks (Sweller, 1988). To face this limitation, subjects turn to cognitive offloading, which means they delegate a portion of information processing to external supports (Risko & Gilbert, 2016). However, Risko and Gilbert (2016) point out that a high cognitive load can trigger a self-reinforcing pattern. Relying on these tools frequently will influence negatively an individual's metacognitive confidence. This drives a drift where technology becomes a systematic alternative to compensate for the limits of one's own memory (Risko & Gilbert, 2016).

In the context of EMI, and particularly within Algeria's complex linguistic landscape where students must simultaneously navigate Arabic, French, and English, this mechanism can emerge as students exert effort on multiple fronts: assimilating course concepts on one hand and decoding multiple foreign languages on the other. This mental strain may be intensified by traditional written assessments requiring unassisted writing compared to flexible, interactive classroom activities that reduce students' performance related anxiety. Faced with this cognitive overload, systematic reliance on external tools such as generative AI risks activating this drift, which will turn what starts as helpful academic support into a dependency reflex for students.

2.5 Self-Perceived Employability in the Modern Era

Self-Perceived Employability (SPE) is defined as *"the individual's perception of his or her possibilities of obtaining and maintaining employment."* (Vanhercke & al., 2014, p. 594). Within Social Cognitive Career Theory (SCCT), Self-Perceived Employability can be conceptualized as a market outcome expectation. This social-cognitive approach aligned with the foundational work of Lent et al. (1994) which posits that students' vocational expectations are determined by the interaction between their self-efficacy beliefs and their cognitive appraisal of environmental supports and barriers within the academic context (Lent & al., 1994). Within our Macro-Meso-

Micro framework, this assessment represents the terminal impact point where top-down EMI policies meet individual student coping behaviors.

Within this cognitive dynamic, the assessment of Self-Perceived Employability (SPE) focuses on the dual-dimensional structure modeled by Rothwell & al. (2008). The first dimension is the internal dimension which captures person-centered attributes and subjective evaluations covering an individual's vocational skills, confidence in their capabilities, and proactive engagement with their academic studies (Rothwell & al., 2008). Significantly, this internal confidence is compromised by the cognitive offloading and AI dependency loops triggered by EMI overloads. The second dimension is the external dimension which reflects contextual and environmental factors covering the perceived strength of the university brand, the general state of the labor market, and the shifting demand for a particular field of study (Rothwell & al., 2008). In the end, students' success expectations are developed based on the intersection of these individual attributes and institutional signals (Rothwell & al., 2008).

From the perspective of Fugate et al. (2004), employability exceeds the simple inventory of academic skills to articulate instead as a form of work-specific active adaptability (Fugate & al., 2004). Within this psycho-social construct, career identity guides the student's *"possible selves"* in the face of environmental signals (Fugate & al., 2004). This theoretical framework takes on full meaning in the current Algerian higher education landscape, where university institutions adopting EMI strive to align themselves with a globalized market that values English proficiency and AI literacy as status markers. Since French has long dominated the country's administrative and corporate sectors. Rather than replacing this language, English acts as an additional layer in the local professional sphere. Students thus see English as a strategic tool to stand out within a market that still largely runs on French.

We summarize the core theoretical framework and key comparative studies in Tables **1** and **2** below.

Table 1. Theoretical Framework Summary

Theory	Key Authors	Focus in Study
New Public Management	Clark (1998)	Macro reforms to micro-outcomes
Social Cognitive Theory	Bandura (1997)	English Self-Efficacy (ESE)
Stress & Coping Theory	Lazarus & Folkman (1984)	AI Dependency (AID)

Cognitive Load Theory	Sweller (1988)	Cognitive Load (CL)
Career Theory (SCCT)	Lent et al. (1994)	Self-Perceived Employability (SPE)

Source: Elaborated by the author based on the literature review.

Taken together, these theories synthesize the complex process through which macro-level governance reforms translate into micro-level student behavioral adaptations. In this context, linguistic self-efficacy, technological adoption patterns, cognitive load constraints, and professional outcome expectations are not isolated. They overlap within the Algerian linguistic landscape, shaping how students navigate institutional demands and define their academic and professional trajectories.

Table 2. Key Comparative Studies

Reference	Objective	Method	Findings	Position of Study
Macaro et al. (2018)	Map global EMI research.	Systematic review.	Notes EMI growth and scarce empirical learning data.	Justifies need for localized data.
Dearden (2014)	Investigate global EMI scale.	55-country survey (British Council).	Highlights gap between macro policies and classroom realities.	Provides macro framework.
Yin et al. (2026)	Examine AI adoption drivers.	SEM survey.	Shows functional student AI use.	Analyzes academic coping strategies.
Rothwell et al. (2008)	Validate employability scale.	Psychometric testing.	Identifies internal/external employability dimensions.	Measures Self-Perceived Employability

Source: Elaborated by the author based on the literature review.

3. RESEARCH METHODOLOGY

3.1 Sampling and Data Collection

Data were collected using an electronic questionnaire distributed via Google Forms, from 21 April to 5 May 2026, just before final exams on 9 May, at the end of students' three-year EMI program. This timing ensured that students completed the full program. We targeted third-year Business Administration students of this EMI program at the University of Algiers 3 deliberately. Every respondent shared the same professors, the same course content, and the same exams.

To assess the adequacy of our sample and the statistical power of our model, we first verified Chin's (1998) 10-times rule for SmartPLS (Fernandes, 2012).This simple rule states that the sample size must exceed 10 times the number of structural paths received by the most complex endogenous construct (Chin, 1998). As required, the sample size comfortably exceeds the minimum requirement of 30 observations for our most complex construct (3×10).

However, following modern methodological guidelines requiring rigorous statistical power checks, a supplementary power analysis was conducted using G-Power 3.1. For a standard structural setup ($f^2 = 0.15, \alpha = 0.05, power = 0.80$) with three predictors targeting Self-Perceived Employability, the unadjusted baseline requires 77 responses. Because our population consists of a fixed pioneer cohort ($N_{pop} = 84$), applying the Finite Population Correction Factor adjusts the minimum threshold to 41 respondents (Cochran, 1977). Our final sample of 69 valid responses covers 82.1% of the entire graduating class.

3.2 Measurement Scales and Construct Specification

The variables we selected in the context of our research are all reflective constructs. Therefore, the items we developed for each variable are direct manifestations of the underlying concepts. These items are therefore interchangeable as well as strongly correlated (Fernandes, 2012).

- ✓ **Self-efficacy in English (ESE):** Based on Bandura's social cognitive theory (Bandura, 1997), we developed this 4-item scale to capture students' subjective beliefs in their capabilities to apprehend business concepts and complete academic tasks exclusively in English (1. I am confident in my ability to understand technical business terms in English. 2. I believe I can express my business ideas clearly during class discussions. 3. I feel capable of passing my tests and final exams in English. 4. I am confident in reading English business textbooks without help.)
- ✓ **Cognitive Load (CL):** Grounded in cognitive load theory (Sweller, 1988) and the cognitive offloading framework (Risko & Gilbert, 2016), we developed this 4-item scale to capture the mental strain and limitations experienced by students in an EMI context (1. I find it mentally exhausting to follow a 90-minute business lecture in English. 2. I am so focused on translating words that I miss the actual business logic. 3. Learning in English requires far more mental effort from me than learning in French or Arabic. 4. I have to re-read my lecture notes multiple times to understand the core meaning.)
- ✓ **AI Dependency (AID):** Grounded in the transactional theory of stress and coping (Lazarus & Folkman, 1984) and self-determination Theory (Yin & al., 2026) ,we developed this 4-item scale to reflect the AI dependency felt by students (1. I rely on AI tools to complete my written assignments in my

English-taught modules. 2. I use AI to translate complex technical texts because I cannot understand them alone. 3. I feel I would fail my English-taught modules if I did not have access to AI tools. 4. I use AI to polish my English because I do not trust my own ability to write professionally.)

- ✓ **Self-Perceived Employability (SPE):** Grounded in social cognitive career theory (Lent & al., 1994) and the dual-dimensional structure of employability (Rothwell & al., 2008), we developed this 4-item scale to capture students' internal and external perceptions of their employment perspectives after graduating from an EMI program (1. I feel confident that my English skills would allow me to secure a job in any international company. 2. I am confident that being able to write professional business reports in English makes me highly employable. 3. I believe that having studied my degree in English gives me a competitive advantage in the job market. 4. I am confident that the market's demand for graduates in English will help me succeed during recruitment selection events.)

4. RESEARCH RESULTS

4.1 Descriptive Statistics

4.1.1 Sample Demographic Profile

Table 3. Consolidated Demographic Profile of the Respondent Cohort (N = 69)

Profile Dimension	Descriptive Category	Frequency (N)	Percentage (%)
Gender	Female	53	76.8%
	Male	16	23.2%
	Subtotal	*69*	*100.0%*
Age Group	Under 20 years	2	2.9%
	20–22 years	64	92.8%
	23 years and above	3	4.3%
	Subtotal	*69*	*100.0%*
Academic Group	Group 27	27	39.1%
	Group 26	21	30.4%
	Group 25	21	30.4%
	Subtotal	*69*	*100.0%*

Source: Synthesized based on IBM SPSS Statistics output (Version 27.0)

The demographic profile indicates a strong female predominance **(76.8%)**. The profile also indicates a high age homogeneity, **92.8%** of the sample are within the **20–22** age bracket. This result confirms that our sample is uniform for bachelor students after a 3-year EMI program without any academic interruption.

4.1.2 Latent Constructs Mean and Standard Deviation

Next, we computed the mean and standard deviation scores for each multi-item construct based on a 5-point Likert scale to examine students' behavioral tendencies within the EMI program.

Table 4. Descriptive Statistics for Latent Constructs (via SPSS v27)

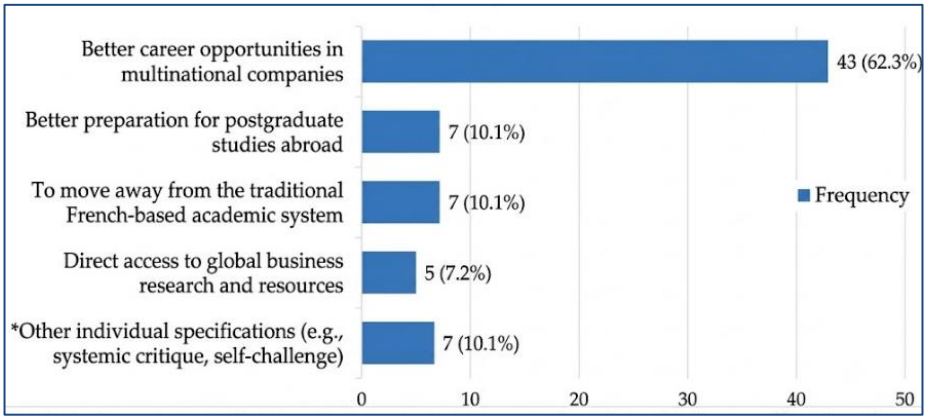
Latent Construct	N	Number of Items	Minimum	Maximum	Mean (M)	Standard Deviation (SD)
English Self-Efficacy (ESE)	*69*	*4*	*1.00*	*5.00*	*3.9855*	*0.79160*
AI Dependency (AID)	*69*	*4*	*1.50*	*5.00*	*3.1449*	*0.74927*
Cognitive Load (CL)	*69*	*4*	*1.00*	*5.00*	*2.5000*	*1.00000*
Self-Perceived Employability (SPE)	*69*	*4*	*1.00*	*5.00*	*4.0145*	*0.81336*

Source: Synthesized based on IBM SPSS Statistics output (Version 27.0).

The results shown in Table **4** show academic and professional confidence of the students. This confidence is characterized by high English Self-Efficacy (M = 3.99) and Self-Perceived Employability (M = 4.01), while Cognitive Load remains manageable for the students (M = 2.50). The 1.50 minimum bound for AI Dependency (M = 3.14) indicates that no single student is completely independent of AI tools. This result established AI tools as generalized support which means they're used across the entire sample to manage the linguistic demands of the EMI program.

4.1.3 Student Motivations for Entering the EMI Track

Fig.1. Primary Motivations for Student Enrollment in the EMI Program (N = 69)



Source: Author's elaboration based on original IBM SPSS Statistics output (Version 27.0).

62.3% of the students chose this EMI program ($n = 43$) to target job opportunities in multinational companies. The traditional French-based system is undergoing a clear pushback, with **10.1%** ($n = 7$) of the sample using this program to break away from it. This result matches the **10.1%** ($n = 7$) that aim for postgraduate studies abroad. Meanwhile, accessing global research resources matters to only **7.2%** ($n = 5$). The final **10.1%** ($n = 7$) represents a mix of personal motives (like self-challenges or shifting away from Arabic) which indicates that career-related motivations outweigh purely academic ones for these students.

4.1.4 Perceived Academic Difficulties in the EMI Track

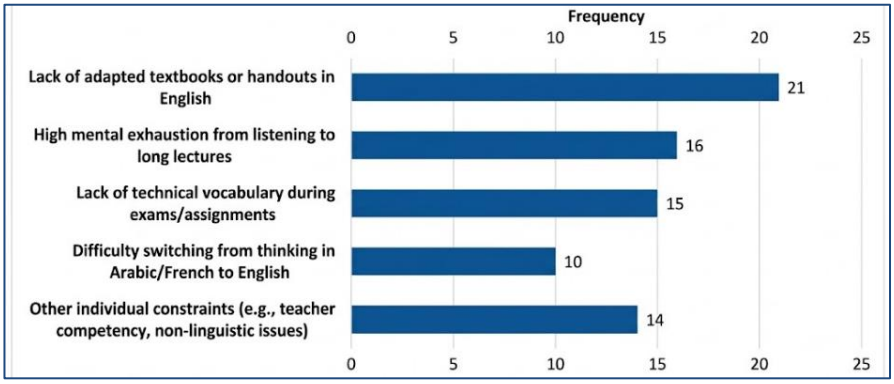


Fig.2. Primary Difficulties Encountered by Students During the 3-Year EMI Program (N = 69)

Source: Author's elaboration based on original IBM SPSS Statistics output (Version 27.0).

When surveyed through a multiple-choice question, students identified

a structural deficit as their primary obstacle: **21** respondents pointed to a lack of adapted English textbooks or handouts. Linguistic and cognitive pressures also ranked high, with **16** counts of high mental exhaustion from long lectures and **15** reports of insufficient technical vocabulary during assessments. Additionally, **10** students struggled with the constant tension due to switching from Arabic/French to English when writing. Finally, **14** responses cited external factors like teacher competency or other non-linguistic issues which demonstrate that transitioning to an EMI program requires considerable resource as well as psychological support.

4.2 Pre-estimation and exploratory factor analysis (IBM SPSS V27)

Before importing the dataset into SmartPLS 4, we performed an Exploratory Factor Analysis (EFA) to ensure data factorability and establish strict scale unidimensionality using IBM SPSS Statistics (v27).

4.2.1 Sampling Adequacy and Factorability Tests

The Kaiser-Meyer-Olkin (KMO) measure and the Bartlett's Test of Sphericity were computed for each measurement scale to determine whether the correlation matrices were suitable for factor extraction.

Table 5. KMO and Bartlett's Test Results (via SPSS v27)

Construct / Scale	KMO Measure	Bartlett's Chi-Square ($\chi 2$)	df	Significance (p-value)
English Self-Efficacy (ESE)	*0.764*	*100.003*	*6*	$p < 0.001$
Cognitive Load (CL)	*0.760*	*88.807*	*6*	$p < 0.001$
AI Dependency (AID)	*0.810*	*103.336*	*6*	$p < 0.001$
Self-Perceived Employability (SPE)	*0.820*	*141.782*	*6*	$p < 0.001$

Source: Synthesized based on IBM SPSS Statistics output (Version 27.0)

According to standard psychometric thresholds, KMO values above **0.70** confirm that the sample is adequate for factor extraction. The high statistical significance of Bartlett's test **($p < 0.001$)** rejects the identity matrix hypothesis which validates the existence of strong organic correlations among the items.

4.2.2 Scale Unidimensionality and Kaiser's Rule

Table 6. Unidimensionality Test Results (via SPSS v27)

Latent Constructs	Number of Items	1st Eigenvalue	2nd Eigenvalue	Total Variance Explained (%)	Kaiser's Rule Decision
English Self-Efficacy (ESE)	4	*2.694 > 1.0*	*0.533 < 1.0*	*66.222 %*	Unidimensional (Confirmed)
Cognitive Load (CL)	4	*2.534 > 1.0*	*0.627 < 1.0*	*63.352 %*	Unidimensional (Confirmed)
AI Dependency (AID)	4	*2.701 > 1.0*	*0.535 < 1.0*	*67.528 %*	Unidimensional (Confirmed)
Self-Perceived Employability (SPE)	4	*2.938 > 1.0*	*0.476 < 1.0*	*73.459 %*	Unidimensional (Confirmed)

Source: Synthesized based on IBM SPSS Statistics output (Version 27.0).

To ensure each multi-item scale reflects a single operational latent variable, the total variance explained was analysed using Kaiser's criterion (Eigenvalues) under SPSS v27. Following the recommendations of Fernandes (2012), scale unidimensionality is confirmed when the first Eigenvalue is strictly greater than **1.0** and the second Eigenvalue is strictly less than **1.0** (Fernandes, 2012). Our results validate unidimensional structure of all variables and justify their insertion into the PLS outer model.

4.3 Evaluation Of The Measurement Model (Outer Model)

We estimated the measurement model by using the standard PLS-SEM algorithm in SmartPLS 4.

4.3.1 Internal Consistency And Convergent Validity

We assessed indicator reliability via item factor loadings, with a required threshold of $> \mathbf{0.70}$ (Hair & al., 2021). We evaluate internal consistency using Cronbach's alpha (α), Construct Reliability (rho_a) and Composite Reliability (rho_c) with a conservative threshold of $\mathbf{0.70}$ or higher (Hair & al., 2021). We established convergent validity through the Average Variance Extracted which requires an $\mathbf{AVE > 0.50}$ (Hair & al., 2021).

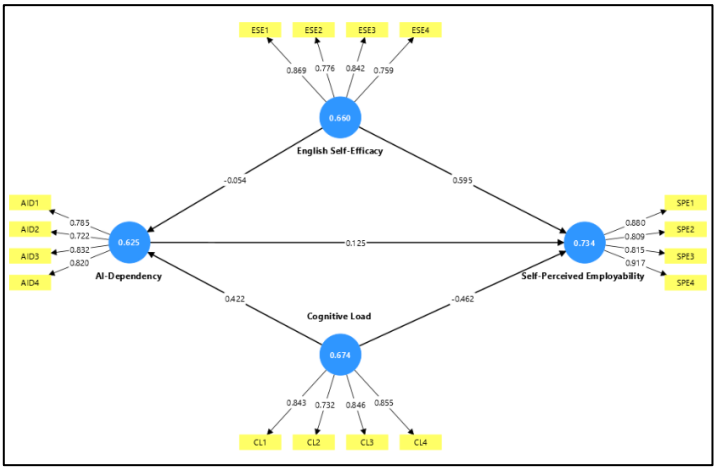
Table 7. Reliability and Convergent Validity Results

Latent Constructs	Items	Outer Loadings	Cronbach's alpha (α)	Construct Reliability (rho_a)	Composite Reliability (rho_c)	AVE
English Self-Efficacy (ESE)	ESE1	*0.869*	*0.829*	*0.850*	*0.886*	*0.660*
	ESE2	*0.776*				
	ESE3	*0.842*				
	ESE4	*0.759*				
Cognitive Load (CL)	CL1	0.843	*0.839*	*0.858*	*0.892*	*0.674*
	CL2	*0.732*				

	CL3	*0.846*				
	CL4	*0.855*				
AI Dependency (AID)	*AID1*	*0.785*	*0.805*	*0.828*	*0.869*	*0.625*
	AID2	*0.722*				
	AID3	*0.832*				
	AID4	*0.820*				
Self-Perceived Employability (SPE)	*SPE1*	*0.880*	*0.879*	*0.903*	*0.917*	*0.734*
	SPE2	*0.809*				
	SPE3	*0.815*				
	SPE4	*0.917*				

Source: Output generated from SmartPLS 4 software using study research data

Fig.3. Measurement Model Assessment (Outer Loadings and Construct Average Variance Extracted)



Source: Output generated from SmartPLS 4 software using study research data.

4.3.2 Discriminant Validity

To verify that each construct represents a distinct empirical reality, the Heterotrait-Monotrait Ratio (HTMT) was implemented. SmartPLS 4 utilizes this metric as a superior alternative to the traditional Fornell-Larcker matrix.

Table 8. Heterotrait-Monotrait Ratio (HTMT) Matrix

Latent Constructs	AI Dependency	Cognitive Load	English Self-Efficacy	Self-Perceived Employability
AI Dependency				
Cognitive Load	*0.493*			

English Self-Efficacy	*0.193*	*0.514*		
Self-Perceived Employability	*0.181*	*0.503*	*0.679*	

Source: Output generated from SmartPLS 4 software using study research data.

The discriminant validity is confirmed. All cross-construct HTMT ratios remain strictly below the conservative threshold of **0.85** (Hair & al., 2021).

4.4 Evaluation of The Structural Model (Inner Model)

The inner model was evaluated. We executed a standard PLS-SEM algorithm to extract both inner and outer VIF for collinearity and Common Method Bias assessment. we also executed a Bootstrapping procedure with **5000** resamples using a two-tailed test at the **5%** significance level to generate stable path coefficients (β, t-statistics, and p-values).

4.4.1 Common Method Bias and Collinearity Assessment

We conducted a Full Collinearity VIF assessment to test for Common Method Bias (CMB) and multicollinearity.

Table 9. Structural Collinearity Assessment (Inner VIF)

Structural Relation	Inner VIF	Result
AI Dependency → Self-Perceived Employability	1.249	No CMB
Cognitive Load → AI Dependency	1.238	No CMB
Cognitive Load → Self-Perceived Employability	1.541	No CMB
English Self-Efficacy → AI Dependency	1.238	No CMB
English Self-Efficacy → Self-Perceived Employability	1.270	No CMB

Source: Output generated from SmartPLS 4 software using study research data.

As shown in Table **9**, all structural VIF values range between **1.238** and **1.541**, remaining strictly below the **3.3** threshold which confirms the absence of Common Method Bias (Kock, 2015).

Table 10. Indicator Collinearity Assessment (Outer VIF)

	Original sample (O)
AID1	*1.453*
AID2	*1.722*
AID3	*2.322*
AID4	*1.629*
CL1	*2.052*
CL2	*1.550*

CL3	*1.841*
CL4	*2.101*
ESE1	*2.207*
ESE2	*1.797*
ESE3	*1.902*
ESE4	*1.624*
SPE1	*2.480*
SPE2	*1.962*
SPE3	*2.023*
SPE4	*3.034*

Source: Output generated from SmartPLS 4 software using study research data.

As shown in Table **10**, all indicator VIF values among the predictor variables are below the critical threshold of **3.3** which confirm the absence of multicollinearity issues (Kock, 2015).

4.4.2 Path Coefficients and Structural Hypothesis Testing

The statistical indicators generated by the bootstrapping algorithm for the five direct structural hypotheses are presented below in the Table **11**:

Table 11. Structural Hypotheses Testing Summary

Hypothesis	Structural Path Relation	Expected Sign	Path Coefficient (β)	Standard Error	T-Statistic	P-Value	Decision
H_1	ESE ⟶ SPE	Positive (+)	*0.434*	*0.123*	*3.527*	*0.000*	Supported
H_2	CL ⟶ SPE	Negative (-)	*-0.407*	*0.153*	*2.657*	*0.008*	Supported
H_3	AID ⟶ SPE	Negative (-)	*0.320*	*0.120*	*2.666*	*0.008*	Rejected (Opposite Sign)
H_4	CL ⟶ AID	Positive (+)	*0.493*	*0.137*	*3.589*	*0.000*	Supported
H_5	ESE ⟶ AID	Negative (-)	*0.162*	*0.152*	*1.061*	*0.289*	Rejected

Source: Output generated from SmartPLS 4 software using study research data

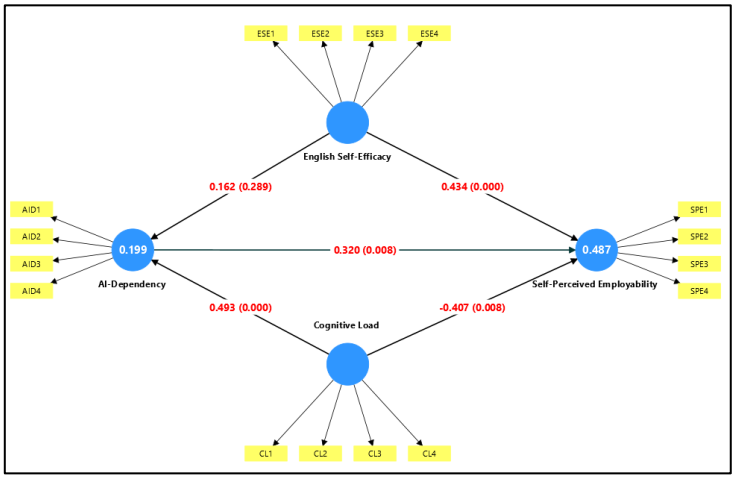
To evaluate the significance of the hypothesized direct paths, we applied critical general thresholds of $\boldsymbol{T > 1.96}$ and $\boldsymbol{p < 0.05}$. Based on these statistical criteria, three hypotheses were supported, while two were rejected under distinct conditions:

✓ Three hypotheses (H_1, H_2, and H_4) were fully supported **($T > 1.96, p < 0.05$)** with their empirical signs aligning perfectly with the hypothesized directions.

✓ **H_3** was rejected due to an opposite sign despite being statistically valid. While the path cleared the significance thresholds, the empirical direction emerged as positive opposing the hypothesized negative impact.

✓ **H_5** was completely rejected due to the non-significance of the structural path as it fails to clear the significance thresholds.

Fig.4. Structural Model Bootstrapping Results (Path Coefficients, P-Values, and R^2 Values)



Source: Output generated from SmartPLS 4 software using study research data.

The structural model yields the following squared multiple correlations (R^2): AI Dependency (AID) **R^2 = 0.199**, and Self-Perceived Employability (SPE) **R^2 = 0.487**. With only three predictors in the model, an R^2 of **48.7%** for Self-Perceived Employability is a solid result. AI Dependency's lower R^2 **(19.9%)** is less surprising than it looks. As a behavioral tendency, it is shaped by many factors, which can be personal, technological, or contextual. In this context, these factors cannot be captured in any single study.

5. DISCUSSION OF THE RESULTS

Our findings reflect students' subjective psychological readiness and self-perceived employability, which should not be confused with actual job placement or guaranteed employment. Our results reveal that bachelor Business Administration students navigating the EMI program must manage three core elements that shape their Self-Perceived Employability: language demands, cognitive strain, and AI tools. Overall, these findings provide an empirical audit of how macro-level public policies translate into micro-level student behaviors.

Hypothesis $\mathbf{H_1}$, which postulated a positive link between English Self-Efficacy (ESE) and Self-Perceived Employability (SPE), is strongly supported ($\beta = 0.434$, $T = 3.527$, $p < 0.05$). This result highlights the importance of student's perception of their English skills for their degree of Self-Perceived Employability. The more students feel capable of mastering English, the more they will perceive finding future employment not as a challenge, but as an opportunity. At the micro-level, this result validates the final objective of the MESRS's macro-policy. It confirms that English confidence directly contributes to heightening professional confidence.

The empirical data supports $\mathbf{H_2}$ which confirms a significant negative relationship between Cognitive Load (CL) and Self-Perceived Employability (SPE) ($\beta = -0.407$, $T = 2.657$, $p = 0.008 < 0.05$). This result shows that the more students face mental strain the less prepared they will feel for employability. Having to translate the content of their courses will drain their energy, thus reducing their self-confidence about their future employability. This negative micro-outcome highlights the gap between the macro-level policies and the operational outcomes for university students.

A key finding of our research lies in the rejection of $\mathbf{H_3}$ in its initially hypothesized negative direction. We started from the assumption that a strong dependence on AI would decrease students' Self-Perceived Employability. However, our results show exactly the opposite. It appears that there is a significant positive relationship between AI dependency (AID) and Self-Perceived Employability (SPE) ($\beta = 0.320$, $T = 2.666$, $p < 0.05$). This result highlights the fact that the more students use AI, the more they will feel prepared for professional world.

This positive relationship points out that in the specific context of Algeria, where the languages used are principally Arabic and French, students are not exposed to professional English. Since the EMI program at the University of Algiers 3 is optional, these students typically arrive with some English skills, but they still have limited exposure to professional business vocabulary. Hence, AI dependency (AID) does not reflect academic laziness or a lack of confidence, but a coping mechanism. To face these limitations, students turn to generative AI tools for language support. In this context, Students perceive AI tools as a compensatory resource rather than a sign of academic failure. These tools can help them enhance their Self-Perceived Employability (SPE).

This aligns with the validation of $\mathbf{H_4}$ ($\beta = 0.493$, $T = 3.589$, $p < 0.05$), the positive relationship between cognitive load (CL) and AI dependency (AID) suggest that the more students go through mental fatigue, the more they turn to AI tools. These results indicate that the use of AI has become a way to manage the mental strain generated by EMI program. By delegating complex writing and comprehension tasks to AI, students may be able to heighten their Self-Perceived Employability (SPE). Here, AI acts as a micro-level technical support that helps students compensate for the language-related limitations.

Finally, the structural path of hypothesis $\mathbf{H_5}$, which postulated that self-efficacy in English (ESE) would reduce dependency on AI (AID), proved to be statistically non-significant ($\beta = 0.162$, $T = 1.061$, $p = 0.289 > 0.05$). This result suggests that students' language level does not significantly impact their use of AI tools. In other words, AI appears to have become a standard academic tool for all students, not just for students who struggle with English. This widespread use demonstrates that the meso-level institutionalization of technology has normalized AI use as an academic standard independently of the student micro-level linguistic capabilities.

6. CONCLUSION

The purpose of this study was to look past macro-level decrees to investigate how higher education governance performs at the micro-level.

Our results show that while English confidence boosts perceived employability, the strain of studying in a foreign language creates a heavy cognitive load. AI dependency does not reflect academic laziness, it serves as a coping mechanism that sustains student confidence when facing linguistic difficulties. Yet this mechanism does not depend on students' English level: the non-significant link between English confidence and AI dependency suggests that generative AI has become a standard tool for all students no matter their English level.

Thus, the University of Algiers 3 stands out for its strategic implementation. This university fostered a framework based on student choice and academic readiness by establishing the EMI program as an optional pathway rather than mandatory. This approach can be qualified as flexible since these students entered this program by choice. In this context, they did not perceive the use of AI as a weakness but as a functional compensatory resource. In the end, by prioritizing student choice, the University of Algiers 3 successfully transformed a demanding educational transition into a driver of perceived professional value.

6.1. Limitations and Future Research Direction

The first limitation of our study lies in the fact that the sample size is relatively small (N=69). While cross-sectional, this sample constitutes **82.1%** of the first pioneer cohort completing the 3-year EMI program upon their graduation in July 2026 (N=69 out of a total population of N=84). This is because the study strictly targeted the pioneer graduating class. While this study captures the most important moment in the EMI program, future research should study larger student populations. Second, we collected the data between April 21 and May 5, 2026, just before the final exams. This timing may temporarily elevate situational cognitive load and AI reliance to face exam-related stress. Third, the study measures student perceptions rather than the actual governance structures. It is an evaluation of the governance structures at the point of impact. Finally, this study measures Self-Perceived Employability rather than actual employment placement.

To address this conceptual gap, future research should opt for a two-year longitudinal tracking study (2026–2028) to follow these specific

graduates into the actual labour market. This will allow future research to verify if their high Self-Perceived Employability translates into actual employment success.

6.2. Strategic Recommendations

To implement the conclusions of our research, the MESRS and the University of Algiers 3 should implement four strategic measures:

- ✓ The University of Algiers 3 should integrate AI literacy into the syllabus of all specialties, this will ensure that students learn to use AI tools correctly, ethically, and within an effective professional framework.
- ✓ The University of Algiers 3 should provide targeted academic English support to address the language-related difficulties that represent over 50% of the cognitive and linguistic barriers reported by students in Fig. 2 (specifically accounting for 41 out of 76 total difficulties including lecture fatigue, vocabulary deficits, and language-switching problems).
- ✓ The University of Algiers 3 must also intensify English training even for professors enrolled in the EMI program. Expanding these training programs and combining them with national digital platforms will help overcome pedagogical difficulties reported by students. This will ensure a smoother EMI transition and address student feedback.
- ✓ Traditional student evaluation methods must evolve. Professors should prioritize oral examinations, real-time simulations, and in-class case studies, while removing take-home presentations, as students rely heavily on generative AI to create them. This will ensure that AI remains a tool for skills development instead of replacing critical thinking.

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