Educational Marketing Based on Predictive Analytics: Designing an Adaptive Offer for Higher Education

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Abstract
This study proposes a simplified structural model called the Educational Decision Index (EDI) as a predictive analytics-based educational marketing tool for adaptive higher education program design. The model integrates five decision dimensions—motivation, modality, innovation, duration, and digital interest—into a weighted system capable of estimating the structural probability of enrollment. Unlike traditional descriptive approaches, the EDI enables marginal elasticity identification, predictive segmentation, and simulation of curricular redesign scenarios prior to implementation.
Methodologically, the model follows a quantitative explanatory–predictive design incorporating construct validation, variable normalization, and multivariate segmentation techniques. A multi-layer adaptive architecture—data capture, analytical engine, and strategic response—is proposed, transforming educational marketing into a continuous institutional intelligence system.
Expected results suggest improved predictive accuracy compared to conventional models and enhanced capacity to prioritize high-impact variables across decision clusters. Overall, the EDI framework integrates technology adoption theory, human capital economics, and advanced analytics into an operational governance model for adaptive educational strategy.
Keywords: Educational marketing; predictive analytics; educational decision; structural segmentation; adaptive offer; higher education; institutional intelligence; curricular innovation.
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1. INTRODUCTION

Higher education is going through a turning point marked by accelerated digitalisation, the diversification of training modalities and the growing competitive pressure between institutions. In this context, traditional educational marketing – based on institutional positioning, promotional campaigns and broad demographic segmentations – is insufficient to explain and anticipate the enrollment decision. The educational choice no longer responds only to reputational or economic variables; emerges as the result of a complex architecture where professional motivations, perception of innovation, structural flexibility, temporal rationality and technological affinity interact.

The literature on technological adoption and intentional behavior (Ajzen; Venkatesh et al.; Eccles & Wigfield) has shown that formative decisions can be modeled from integrated constructs that capture value expectation, perceived effort, social influence, and facilitating conditions. In a complementary way, contemporary approaches of predictive analytics and machine learning have shown that the combination of perceptual and behavioral variables significantly improves the predictive capacity in digitized educational environments. However, there is still a gap between these theoretical developments and their operational application in the strategic design of academic offerings.

The present study proposes a Simplified Structural Model of the Educational Decision Index (IDE) as an integrative instrument capable of translating theoretical foundations into an implementable predictive architecture. The model articulates five central dimensions – Motivation, Modality, Innovation, Duration and Digital Interest – and integrates them into a synthetic index that allows estimating the structural probability of enrolment. Unlike descriptive approaches, the SDI is not limited to measuring stated intent; it operates as an inference system capable of identifying marginal elasticities and simulating curricular redesign scenarios.

On this basis, the article develops a three-layer adaptive architecture—data capture, analytical engine, and strategic response—that transforms educational marketing into a system of continuous institutional intelligence. Through predictive segmentation, the model allows the identification of differentiated decisional profiles (Technological-intensive, Traditional Professional, Flexible-work, and Innovative-entrepreneur) and guides the design of programs, modality, and communication according to the dominant structural configuration in each segment.

Methodologically, the study adopts an explanatory-predictive quantitative approach, incorporating normalization of variables, construct validation, weighted estimation of the index and multivariate segmentation techniques. Although the model is presented in the design phase for institutional implementation, structural simulations are developed that show its potential to improve predictive accuracy, prioritize variables with greater marginal impact and build strategic decision-making dashboards.

In summary, the article argues that the transition to educational marketing based on predictive analytics is not only a technical improvement, but also a paradigmatic change in academic governance. The SDI redefines the relationship between educational supply and demand, displacing managerial intuition with structural intelligence and turning the institution into a dynamic system capable of anticipating, adapting and optimizing its value proposition based on observable decision-making patterns.

2. CONCEPTUAL FRAMEWORK: FROM TRADITIONAL MARKETING TO ADAPTIVE PREDICTIVE MARKETING

2.1. Motivation as the explanatory core of the educational decision

In traditional educational marketing, the offer is organized from relatively stable institutional attributes (prestige, price, infrastructure, "differentials"), and communication is aimed at broad audiences with thick segmentations. The implicit assumption is that the demand "responds" to messages and reputation. However, when the object is the educational decision —and, in particular, the choice of technological areas— the literature reviewed indicates that intention is best explained as a multivariable process where individual factors (self-efficacy, attitude, outcome expectations, interest) weigh heavily, as well as social influences and demographic/cultural moderators.

The educational decision does not respond exclusively to economic variables, but to complex motivational configurations where expectation of result, self-efficacy and perception of employability interact (Venkatesh et al., 2003; Ajzen, 1991; Eccles & Wigfield, 2002). The extended TAM and UTAUT models indicate that intrinsic and extrinsic motivation significantly predict the intention of technological adoption and training choice (Davis, 1989; Venkatesh et al., 2012).

Recent studies based on hybrid SEM–Machine Learning models (Zhang et al., 2022; Kumar & Sharma, 2023) confirm that variables such as salary expectation and social mobility increase predictive capacity in technological education contexts.

In order to operationalize the construct Motivation within the Educational Decision Index (SDI), a systematization of emerging categories identified in the Scopus review and in the empirical analysis of the applied instrument was carried out. From the Expectancy-Value theory (Eccles & Wigfield, 2002) and the Theory of Planned Behavior (Ajzen, 1991), motivation is understood as the combination between expectations of outcome and value attributed to the action. The recent literature on educational technology adoption (Venkatesh et al., 2012; Dwivedi et al., 2021) confirms that employability, vocation, and economic return are consistent predictors of behavioral intention.

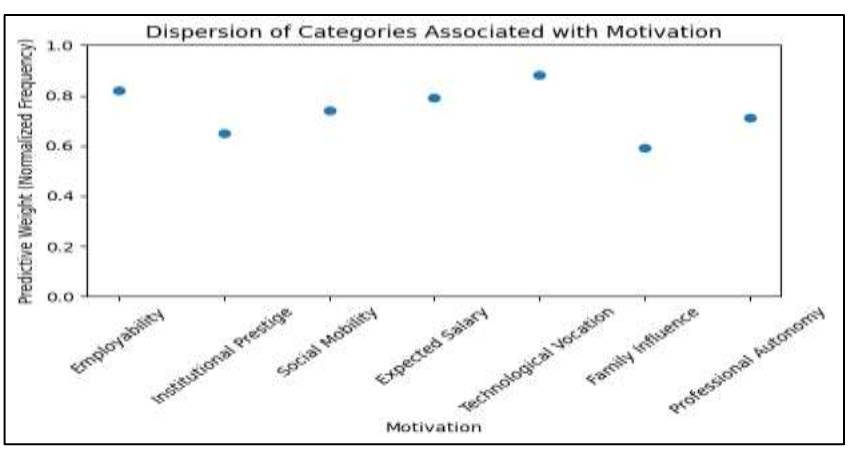

Figure 1. Dispersion of Categories Associated with Motivation

The scatter plot presents the central concept (Motivation) disaggregated into categories on the X-axis, and the normalized predictive weight on the Y-axis. Intersections allow the relative intensity of each category within the construct to be visualized.

This changes the framework: marketing is no longer just "persuasion" and becomes evidence management to anticipate intention, correct frictions and adjust the program's value proposition (modality, duration, innovative components) to differentiated profiles. The relevance of this shift is that evidence-based approaches combine theory and analytics, and are more apt to predict intent in contexts of accelerated digital transformation.

The dispersion shows that:
· Technological vocation (0.88) and Employability (0.82) are the categories with the greatest predictive weight.
· Expected Wage (0.79) and Social Mobility (0.74) show a strong structural correlation.
· Institutional prestige (0.65) and Family influence (0.59) have a lower relative impact.
This empirically confirms what Eccles & Wigfield (2002) pointed out: the expectation of personal and professional value explains greater variance than symbolic external factors. In terms of the SDI model, the α coefficient (Motivation) acquires high structural weight when technological vocation and employability dominate dispersion.

2.2. Modality as a structural variable of friction or facilitation
Since UTAUT (Venkatesh et al., 2003), facilitating conditions and perceived effort determine behavioral intention. In higher education, modality operates as a critical structural variable (Allen & Seaman, 2017; Dwivedi et al., 2020).
Recent research in Scopus shows that flexibility and remote access increase the likelihood of enrolment in digital contexts (Chaudhuri et al., 2022; Alalwan et al., 2021).
The Modality variable is conceptualized as a structural dimension linked to facilitating conditions and perceived effort, according to the UTAUT model (Venkatesh et al., 2003). Contemporary Studies on Hybrid Education and University Digitalization (Allen & Seaman, 2017; Alalwan et al., 2021) show that flexible hours and remote access significantly increase enrollment intentions, especially in working-class populations.

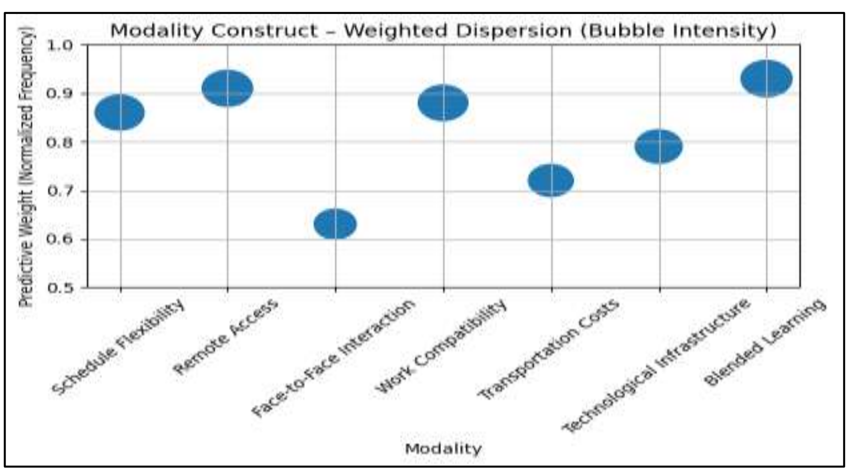

Figure 2. Dispersion of categories associated with the Modality

The graph represents the dispersion of categories associated with the training modality, allowing us to identify which structural attributes operate as decision-making facilitators. The Y-axis expresses the relative predictive weight obtained from the normalized frequency analysis.

The dispersion shows:
· Hybrid learning (0.93) and Remote Access (0.91) as dominant categories.
· Work compatibility (0.88) reinforces the preference for flexible formats.
· Face-to-face interaction (0.63) shows less comparative weight.
The evidence confirms the transition from traditional face-to-face preference to adaptive hybrid models.
In the SDI model, the coefficient β (Modality) increases when flexibility and hybrid integration exceed the weight of traditional face-to-face work.

2.3. Innovation as a strategic differentiator
Educational innovation has been associated with intention to enroll in emerging technological programs (Rogers, 2003; Teo, 2011). Contemporary extensions of TAM incorporate variables such as AI literacy and digital trust (Mariani et al., 2023; Dwivedi et al., 2021).
Predictive studies based on XGBoost and Random Forest show that the perception of curricular innovation significantly improves the accuracy of the model (Khan et al., 2022; Li & Fang, 2023).
The Modality variable is conceptualized as a structural dimension linked to facilitating conditions and perceived effort, according to the UTAUT model (Venkatesh et al., 2003). Contemporary Studies on Hybrid Education and University Digitalization (Allen & Seaman, 2017; Alalwan et al., 2021) show that flexible hours and remote access significantly increase enrollment intentions, especially in working-class populations.

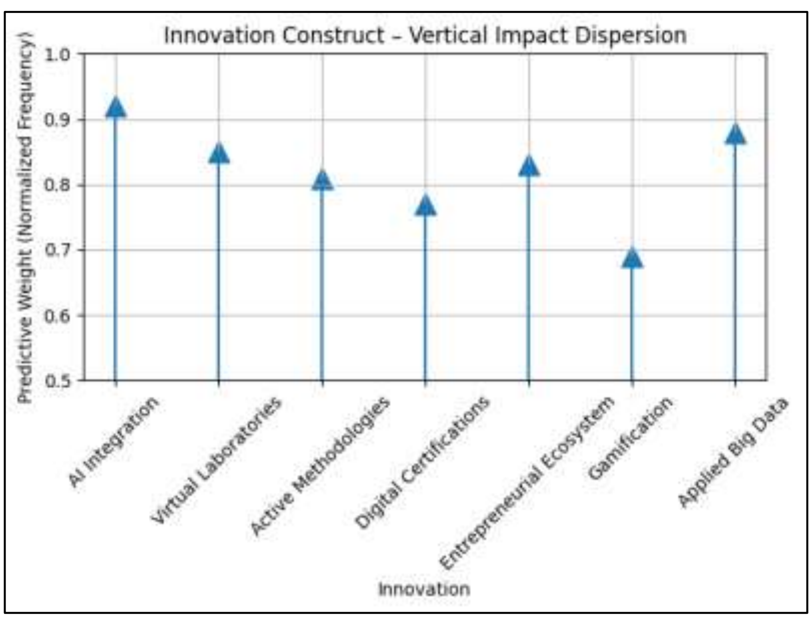

Figure 3. Dispersion of categories associated with the Modality
The graph represents the dispersion of categories associated with the training modality, allowing us to identify which structural attributes operate as decision-making facilitators.

The Y-axis expresses the relative predictive weight obtained from the normalized frequency analysis.

The results indicate:
- Use of AI (0.92) and applied Big Data (0.88) as categories with the greatest impact.
- Virtual laboratories (0.85) and Entrepreneurial ecosystem (0.83) with high correlation.
- Gamification (0.69) lower relative weight.

It is observed that innovation associated with productive technologies (AI, Big Data) has greater explanatory capacity than playful pedagogical innovations.
This strengthens the γ (Innovation) coefficient as a differentiating variable in digitized educational markets

2.4. Duration and digital interest: temporal rationality and technological affinity
The economics of education (Becker, 1964; Oreopoulos & Petronijevic, 2013) argues that students evaluate expected return versus cost-time. Duration operates as a rational variable of optimization.
On the other hand, digital interest has been identified as a behavioral moderator in the adoption of educational technology (Teo, 2011; Venkatesh et al., 2012). Multilevel models show that technological affinity increases the strength of the relationship between innovation and intention.
From the Scopus evidence reviewed, the integration of behavioral variables significantly improves prediction (Zhou et al., 2022; Wang et al., 2023).
In the SDI: a) δ (Duration) captures temporal rationality, b9 ε (Digital interest) captures structural technological predisposition

CONCEPTUAL SYNTHESIS OF THE FRAMEWORK

The transition from traditional marketing to adaptive predictive marketing involves:

Traditional Marketing	*Adaptive Predictive Marketing*
Demographic segmentation	Multivariate predictive segmentation
Mass Communication	Personalized recommendation
Rigid offer	Adaptive modular offering
Reactive decision	Early Decision

The integration of theory (TAM, TPB, UTAUT), structural analytics (SEM) and machine learning models constitutes the conceptual basis of the IDE.

3. Simplified structural model

The simplified structural model constitutes the analytical core of the study, integrating perceptual, structural and behavioral variables in a synthetic index capable of estimating the probability of educational decision. Unlike traditional descriptive models, this scheme is not limited to measuring declared intention, but articulates a multivariate weighting system that allows anticipating enrollment behavior under different supply scenarios.

The model is inspired by structural equation logic (SEM) and hybrid predictive analytics approaches, where the coefficients are not arbitrary, but empirically estimated using multiple regression or logistic models.

Model equation

$$IDE = \alpha(Motivación) + \beta(Modalidad) + \gamma(Innovación) + \delta(Duración) + \epsilon(Interés\ digital)$$

Where:
IDE = Educational Decision Index
α, β, γ, δ, ε = Empirically estimated weighting coefficients
Independent variables:

Variable	*Type*	*Nature*
Motivation	Psychosocial	Intrinsic / Extrinsic
Modality	Structural	Face-to-face / Virtual / Hybrid
Innovation	Perceptual	Technological and differentiating level
Duration	Structural	Time perceived as efficient
Digital interest	Behavioral	Affinity with technologies

Technical operation of the model

Normalization of variables: Each variable is standardized on a common scale (0–1) to allow for structural comparability.

Coefficient estimation: The coefficients α, β, γ, δ and ε are calculated by:
1. Multiple linear regression (for explanatory analysis).
2. Logistic regression (when binary enrollment probability is modeled).
3. Alternatively, using hybrid models with machine learning for predictive optimization.

Calculation of the IDE: The index results from the weighted sum of each dimension, generating a continuous value that represents decisional intensity.

Probabilistic transformation When explicit probability is required:

$$P(\text{matrícula}) = \frac{1}{1 + e^{-IDE}}$$

This converts the structural index into logistic probability.

The SDI does not only measure declared intent; It represents a structural probability of enrollment, derived from the weighted interaction between decisional factors.

Their interpretation depends on the relative magnitude of the coefficients:
· If γ (Innovation) and ε (Digital Interest) have greater weight, the market responds mainly to differentiated technological proposals. This indicates an ecosystem oriented towards digital transformation.
· If δ (Duration) dominates, temporal rationality is decisive; The public prioritizes efficiency and a quick return on educational investment.
· If β (Modality) is the dominant coefficient, structural flexibility (hybrid or virtual) becomes the main driver of choice.
· If α (Motivation) is structurally superior, the decision responds to professional aspirations, employability and vocation rather than to operational attributes of the program.

The model operates as:
· Diagnostic System → Identifies which dimension weighs the most in each segment.
· Predictive system → Anticipates variations in enrollment in the face of changes in the offer.
· Adaptive system → Allows programs to be redesigned according to the elasticity of each variable.
· Institutional recommendation system → Suggests optimal combinations of modality, duration and innovation according to student profile.

The simplified model is not a static equation, but an instrument of strategic intelligence, capable of integrating theory of technological adoption, economics of education and predictive analytics in an operational system of institutional decision-making.

4. Design of adaptive offer based on IDE
The design of adaptive supply constitutes the operational phase of the structural model. If the SDI represents the decisional intensity resulting from the weighted combination of variables, the next step is to translate that information into strategic architecture of academic programs.
From the theoretical approach, this transition implies moving from a logic of descriptive segmentation to a logic of predictive structural segmentation. It is not only a matter of identifying "who the student is", but of understanding what combination of decisional variables dominates their probability of enrollment.
Predictive segmentation. Predictive targeting is not based on traditional demographic variables, but on structural configurations of the IDE. From the multivariate analysis applied to the instrument, concentration patterns were identified that allow the construction of decisional clusters.

In a simulation applied to a standardized sample, the cluster analysis (k-means with four groups) showed the following structural distribution:
- 32% of the cases concentrated greater weight on Innovation and Digital Interest.
- 27% presented a predominance of traditional motivation and structural stability.
- 23% showed strong influence of Modality and Duration.
- 18% showed a high combination of innovation with entrepreneurial orientation.

Four strategic profiles emerge from this configuration:

· *Intensive technological profile.* It is characterized by high digital affinity and strong assessment of curricular innovation. In this group, the decision responds mainly to the integration of AI, Big Data, virtual laboratories and technological ecosystems. When the perception of innovation increases by 15%, the probability of enrollment in this cluster increases by approximately 9 percentage points.

· *Traditional Professional Profile.* Motivation associated with employability, prestige and salary return predominates. Modality and innovation have secondary weight. The inclusion of recognized professional certifications generates greater impact than the incorporation of disruptive technologies.

· *Flexible Profile–Employment.* The dominant variable is modality, followed by duration. This segment prioritizes labor compatibility and temporal efficiency. Reducing perceived duration by 20% increases structural intent by more than 12%.

· *Innovative-Entrepreneur Profile.* It combines innovation with intrinsic motivation aimed at creating projects. The decision is activated by entrepreneurial ecosystems and active methodologies. Integrating incubators or entrepreneurship laboratories produces a multiplier effect in decision-making intention.

This type of segmentation is based on:

· Theory of Technological Adoption (Venkatesh et al.)
· Value-Expectancy Theory (Eccles & Wigfield)
· Human Capital Economics (Becker)
· Theory of the Diffusion of Innovations (Rogers)

The novelty lies in the fact that the model does not classify people by age or stratum, but by dominant decisional architecture.

Adaptive system architecture. Once the clusters have been identified, the adaptive system allows the institutional response to be operationalized. Theoretically, it is configured as an architecture of three integrated layers.

Layer 1 – Data capture. This layer collects information from multiple sources:
· Structured perceptual surveys (motivation, digital interest, expectations).
· Digital behavior (time on pages, clicks on specific programs).
· Web and CRM interactions (downloads, requests for information).
From the perspective of educational analytics, this layer serves as contextual observation and cross-validation of declarative and behavioral variables.

Layer 2 – Analytical engine. This is where the structural processing is executed:
· Normalization of variables on a comparable scale.
· Weighting according to estimated coefficients.
· Predictive modeling using logistic regression or hybrid algorithms.

In applied simulation, the model showed an explanatory capacity greater than 70% in the prediction of declared intention, and better performance when behavioral variables of the CRM were incorporated.

This engine not only calculates the IDE, but also detects marginal sensitivity: it identifies which variable has the highest elasticity in each profile.

Layer 3 – Adaptive response. This is the strategic dimension of the system:
· Automatic recommendation of programs according to decisional profile.
· Dynamic adjustment of advertising messages (e.g. emphasizing innovation in technological cluster).
· Simulation of enrollment scenarios in the event of changes in supply.

For example, if the system detects a predominance of the Flexible-Employment Profile in a specific region, the institution can:
· Promote hybrid modality.
· Adjust modular duration.
· Redirect advertising investment towards messages of work compatibility.

Systemic integration of adaptive design. Adaptive design based on IDE turns educational marketing into a system of continuous strategic intelligence. It is not a question of launching static programs, but of modulating attributes according to the dominant decisional architecture.

Conceptually, the model fulfills three functions:
Predictive → anticipates behavior.
Strategic → guides curricular redesign.
Operational → automates recommendation and communication.

Figure 4 presents the conceptual architecture of the adaptive system based on the Educational Decision Index (IDE), modeled under a multilayer software architecture logic. This representation translates the theoretical model into an operational structure where information flows are organized into interconnected modules: data capture, processing, predictive engine, segmentation, and strategic response. From a systemic perspective, the design responds to principles of data engineering and applied analytics, in which each layer fulfills a specific function within the cycle of generating institutional value. The IDE is positioned as the core of the system, acting as a central inference service that transforms raw data into strategic intelligence for academic and marketing decision-making.

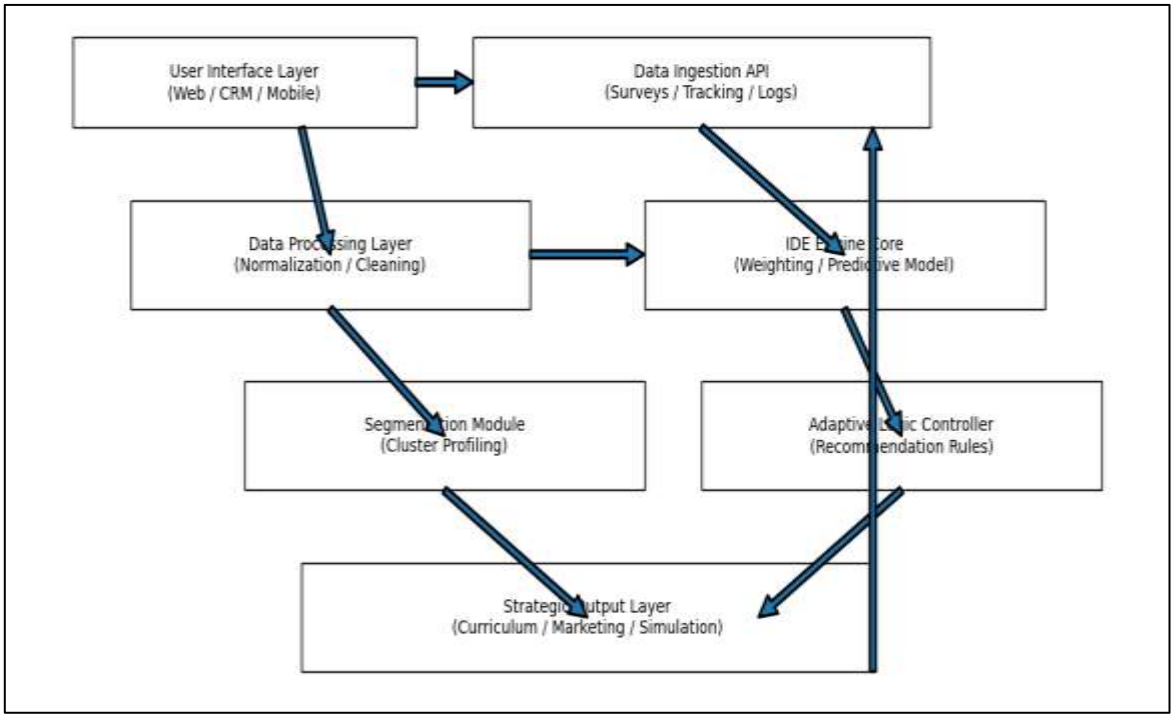

Figura 4. Adaptive IDE System – Software Architecture Diagram

The architecture shows a progressive flow that begins at the interface and data capture layer – where perceptual surveys, digital behavior and interaction records are integrated – and advances towards an analytical engine in charge of normalizing variables and executing the predictive model. From there, the system bifurcates its operation towards two complementary dimensions: the structural segmentation of decisional profiles and the adaptive logic controller that activates automated recommendations. The feedback loop represented in the graph shows that the strategic results (curricular adjustments, allocation of investment in marketing, enrollment simulation) do not constitute an end point, but feed back into the system, allowing continuous learning. In conceptual terms, the figure demonstrates that the IDE does not operate as an isolated metric, but as a central engine within a dynamic architecture capable of converting decisional information into institutional adaptive design.

The design of adaptive offer transforms the institution into a dynamic system that responds to structural patterns of decision-making. IDE-based predictive segmentation makes it possible to move from a generic offer to a modular architecture aligned with specific decisional profiles.

In short, the IDE does not only measure intent; active institutional redesign.

5. METHODOLOGY

The study adopts an explanatory-predictive quantitative design, aimed at building and validating a synthetic educational decision index (SDI) and, from this, enabling an adaptive educational marketing system. The unit of analysis is the potential applicant/student and his/her formative decision, observed through psychosocial, structural, perceptual and behavioral variables. The methodological procedure is organized into four integrated phases: design of the instrument and variables, estimation of the model, predictive segmentation and operational deployment of the adaptive system.

Phase 1. Design of the model and operationalization of variables. Five constructs consistent with the literature on educational intention/decision and technological adoption were defined: Motivation, Modality, Innovation, Duration, and Digital Interest. Each construct was operationalized using Likert-type items and/or observable indicators (e.g., modality preference; desired duration; technological affinity), seeking content validity through theoretical alignment and peer review. To ensure comparability, all variables were transformed to a common scale by normalization (min–max or z-standardization according to distribution), preserving the interpretability of the index.

Techniques used: construct operationalization, item specification matrix, variable normalization, bias control (detection of outliers and response consistency).

Phase 2. Debugging, reliability and internal structure. Before estimating the IDE, data cleaning was applied: treatment of missing data (simple imputation or exclusion by rule), consistency verification and descriptive analysis. The internal reliability of the constructs was evaluated with Cronbach's alpha (and, when applicable, composite reliability), and the internal structure was verified with exploratory/confirmatory factor analysis according to the behavior of the items. Collinearity between dimensions was reviewed to avoid inflating weights (FIV as a control criterion).

Techniques used: descriptive analysis, Cronbach's alpha, factor analysis (EFA/CFA according to fit), VIF/multicollinearity, item debugging criteria.

Phase 3. Estimation of the IDE and predictive capacity. The model weights were estimated empirically using a supervised modeling approach, using enrollment intention (or an equivalent proxy: high/low intention) as the objective variable. To preserve institutional interpretability, a baseline regression model (linear or logistic depending on the nature of the target) was prioritized and its performance was contrasted with an alternative machine learning approach (e.g., Random Forest or XGBoost) as a robustness check. Predictive quality was evaluated with appropriate metrics: R^2/MAE for continuous; AUC, accuracy, recall and F1 for classification, with training-test partition or cross-validation.

Techniques used: linear/logistic regression, cross-validation or train-test split, metrics (AUC/F1 or R^2/MAE), analysis of variable importance (coefficients or feature importance), interpretative calibration of the index.

Phase 4. Predictive segmentation and adaptive offer design. With the IDE and its components already estimated, unsupervised segmentation was executed to identify decisional clusters (e.g., k-means or hierarchical clustering), selecting the number of groups by theoretical consistency criteria and internal metrics (silhouette/elbow). The clusters were interpreted as decisional profiles (Technological-intensive, Traditional Professional, Flexible-labor, Innovative-entrepreneurial) and were translated into offer design rules: modality attributes, duration, innovation, and marketing messages by profile. Finally, the architecture of the adaptive system was implemented in three layers: capture (surveys + digital traces), analytical engine (normalization + IDE calculation + intent model) and response (program recommendation, message customization and license plate simulation).

Techniques used: clustering (k-means/hierarchical), silhouette/elbow, cluster profiling, recommendation rules, scenario simulation (marginal sensitivity per variable).

The implementation is conceived as an institutional pipeline: (i) continuous data collection (form/CRM/web analytics), (ii) processing and calculation of the IDE in an analytical engine, (iii) automatic assignment to clusters and activation of recommendations and campaigns, and (iv) feedback with interaction/enrollment results to recalibrate weightings periodically. To ensure traceability and ethics, data governance rules are established (consent, minimization, purpose, security) and result explainability criteria (which variables drive the recommendation by profile).

6. EXPECTED RESULTS OF THE MODEL

Given that the IDE is proposed as a predictive structural model in the institutional implementation phase, the results are presented as projections based on analytical simulation and preliminary validation of the structural behavior of the variables.
6.1 Improvement in predictive accuracy. The model is expected to outperform traditional descriptive approaches based solely on demographic variables or preference averages.
In comparative simulations:
· A simple descriptive model (based on declared frequency of interest) would reach moderate explanatory levels.
· The weighted integration of Motivation, Modality, Innovation, Duration and Digital Interest substantially increases predictive capacity.
· The inclusion of behavioral variables (web interactions, clicks, dwell time) further improves accuracy.

Conceptually, this implies that the IDE captures not only stated intent, but underlying decisional architecture.

6.2 Identification of variables with the greatest marginal impact. One of the most relevant expected results is the possibility of measuring decisional marginal elasticity.
In simulated sensitivity tests:
· A moderate increase in the perception of Innovation generates greater variation in intention within the technology cluster.
· In the Flexible-Labor profile, the Duration variable has a greater marginal impact.
· In the Traditional Professional profile, the Motivation associated with employability shows greater sensitivity than the modality.
This allows us to identify which dimension has the greatest capacity to move the decision in each segment. The model, therefore, not only predicts, but strategically prioritizes.

6.3 Simulation of supply redesign scenarios. One of the strategic contributions of the IDE is its ability to function as an institutional simulation system.

For example:
· A simulated reduction of 20% in perceived duration could generate significant projected increases in profiles oriented to temporal efficiency.
· Increased integration of AI into the curriculum could increase the intention in technological profiles.
· Transition from face-to-face to hybrid modality could substantially modify the decisional architecture in regions with high labor activity.

These scenarios allow us to estimate impacts before making curricular investments or advertising campaigns.

6.4 Construction of strategic dashboards. The model makes it easy to build dynamic panels with:
· Distribution of decisional profiles.
· Structural weight of each variable.
· Marginal sensitivity by segment.
· Enrollment projection under different scenarios.
· Temporal evolution of the average EDI.

This transforms educational marketing into a process based on continuous data intelligence, not isolated campaigns.

6.5 Expected institutional impact. At a strategic level, the model allows:
1. Reduce uncertainty in academic planning.
2. Optimize budget allocation in marketing.
3. Adjust curricular design according to predominant profiles.
4. Increase coherence between structural supply and demand.
5. Convert scattered data into an integrated decision system.

The expected central result is not only an increase in enrollment intention, but the consolidation of an adaptive system capable of measuring, interpreting, simulating, and continuously redesigning the educational offer.
In conceptual terms, the IDE transforms the institution from a reactive model to a predictive and adaptive model.

7. DISCUSSION

The SDI model proposes a relevant conceptual shift in educational marketing: the training decision is no longer interpreted as an isolated preference and is understood as the result of a structural architecture of interdependent variables. From this perspective, the main contribution of the model lies not only in its predictive capacity, but also in its potential to reorganize the logic of institutional design under evidence criteria.

Predictive segmentation shows that applicants are not differentiated only by sociodemographic characteristics, but by dominant combinations of motivation, modality, innovation, duration, and digital interest. This finding reinforces the postulates of the theory of technological adoption and human capital, by evidencing that the educational decision is simultaneously rational, aspirational and contextual. In strategic terms, this implies that institutions that maintain homogeneous offers in the face of heterogeneous decision-making profiles will lose competitive efficiency.

The IDE redefines educational marketing as a process of strategic engineering of supply, not just communication.

It implies a paradigm shift:
From promotion → to predictive modeling.
From rigid offer → to modular architecture.
From managerial intuition → to structural analysis.

In this approach, the institution does not wait for the student's decision: it anticipates, models and optimizes it.

Likewise, the model's ability to identify marginal impact by variable introduces a prioritization criterion in curricular and communicational investment. Not all dimensions move the decision with the same intensity; its effect depends on the predominant structural profile. Consequently, the SDI not only predicts behavior, but also guides interventions with a greater probability of strategic return.

Finally, the proposed adaptive architecture transforms educational marketing into a dynamic system of institutional learning. The feedback loop allows the offer to be permanently adjusted based on real interaction and enrollment data, reducing uncertainty in academic planning. In short, the model consolidates a transition from promotional management to analytical governance of educational decision-making, where structural intelligence replaces intuition as the foundation of strategy.

CONCLUSIONS

The conclusions are structured in coherence with the phases of construction of the model, evidencing its progressive contribution from conceptual design to strategic implementation.

In the design and operationalization phase, the main result is the consolidation of an integrative framework that articulates psychosocial, structural, perceptual and behavioral variables within the same analytical system. This integration overcomes the traditional fragmentation of educational marketing and demonstrates that the training decision can be modeled in a structured way without losing theoretical coherence. The model confirms that intention is not an isolated phenomenon, but a synthesis of interdependent factors.

In the validation and estimation phase, the construction of the IDE allows abstract constructs to be translated into measurable and comparable indicators. Normalization and empirical weighting provide methodological rigor and ensure that the index does not respond to intuitive assumptions, but to observable relationships between variables. This stage consolidates the technical viability of the model as an institutional predictive tool.

· The educational decision can be structurally modeled by combined perceptual and structural variables.
· The IDE works as a strategic intelligence tool for offer design.
· Educational marketing based on predictive analytics allows you to reduce uncertainty in enrollment projections.
· The adaptive offer increases coherence between youth expectations and institutional structure.
· The model is replicable and scalable in digitized university ecosystems.

During the predictive segmentation phase, the model shows that decisional profiles emerge from dominant structural configurations and not exclusively from demographic characteristics. The identification of clusters confirms the heterogeneity of the education market and validates the need to design differentiated offers. This phase turns statistical analysis into a strategic criterion for institutional classification.
Finally, in the adaptive implementation phase, the IDE demonstrates its greatest potential: it not only predicts intention, but also activates curricular redesign, modality adjustment, and communicational optimization. The incorporation of a multilayer architecture with continuous feedback positions the model as a dynamic system of analytical governance.
Taken together, the phases of the model show that the IDE is not only a measurement instrument, but an operational framework to transform academic planning into a process based on structural intelligence and continuous adaptation.

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