STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **x**, Month 202x, pp 0–12.
Published online in International Academic Press (www.IAPress.org)

A Statistical and Optimization Based Framework for Evaluating Digital Learning Platforms Using Student Survey Data

Zouhair Ouazene [1,*], Amina Karroum [2], Jamal Amraoui [1], Rachida Gougil [2]

[1] *Sidi Mohamed Ben Abdellah University, Fez, Morocco*
[2] *Applied Human Sciences Laboratory, Higher Normal School, Sidi Mohamed Ben Abdellah University, Fez, Morocco*

Abstract The increasing adoption of digital learning platforms in higher education has led to the widespread use of student survey data to assess learning experiences and outcomes. While such data provide valuable insights into learners perceptions, their analytical potential is often under exploited due to the predominance of descriptive approaches. This paper proposes a statistical and optimization-based framework for evaluating digital learning platforms using student survey data. Perceived learning improvement is modeled as an ordinal response variable influenced by multiple explanatory factors, including accessibility, motivation, content adequacy, technical constraints, time availability, and external practice. The empirical analysis relies on survey data collected from 300 undergraduate students and combines multivariate regression modeling with exploratory factor analysis to identify key determinants and latent dimensions underlying student perceptions. The statistical results are subsequently embedded within an optimization framework that formalizes learning effectiveness as an objective function under practical resource constraints. The findings indicate that motivation and content adequacy are the factors most strongly statistically associated with perceived learning improvement, while technical constraints exert a negative but secondary effect. By integrating statistical inference with optimization-oriented reasoning, the proposed framework provides a structured and decision-relevant approach for the quantitative evaluation of digital learning platforms in higher education.

Keywords Digital learning platforms; Student survey data; Statistical modeling; Factor analysis; Optimization framework; Decision-oriented evaluation

AMS 2010 subject classifications 62P25, 62J05, 62H30, 68T05.

DOI: 10.19139/soic-2310-5070-3396

1. Introduction

The rapid proliferation of digital learning platforms has significantly reshaped contemporary higher education systems. Initially introduced as pedagogical support tools, these platforms have progressively evolved into complex socio-technical systems that generate large volumes of structured and semi-structured data related to learners behaviors, perceptions, and learning outcomes. This transformation raises fundamental scientific questions regarding how such platforms should be evaluated, compared, and optimized, not only from an instructional perspective but also through rigorous statistical and optimization-based frameworks. In recent years, student survey data have emerged as a valuable source of information for understanding learning processes in digital environments. These data capture latent dimensions such as motivation, perceived usefulness, accessibility, and satisfaction, which are difficult to observe directly but play a decisive role in learning effectiveness. From a statistical viewpoint, these dimensions form a multivariate inference problem, where learning outcomes are influenced by multiple interdependent explanatory factors. However, much of the existing research on digital learning platforms remains confined to descriptive analyses or isolated hypothesis testing, limiting its capacity

[*]Correspondence to: Zouhair Ouazene (Email: zouhair.ouazene@usmba.ac.ma). Sidi Mohamed Ben Abdellah University, Fez, Morocco.

ISSN 2310-5070 (online) ISSN 2311-004X (print)

to support robust institutional decision-making. From an optimization and information computing perspective, evaluating digital learning platforms extends beyond measuring average satisfaction or usage rates. It involves identifying key leverage variables, quantifying their relative statistical relationships with perceived learning improvement, and exploring how limited educational resources may be theoretically allocated within the proposed optimization framework. This framing naturally positions the evaluation problem at the intersection of statistics, optimization, and data-driven decision theory, which constitutes the core scope of *Statistics, Optimization & Information Computing*. Despite the growing interest in educational data analytics, there remains a noticeable gap in the literature concerning the integration of statistical modeling and optimization-based reasoning in the evaluation of digital learning platforms using student survey data. Existing studies often emphasize pedagogical interpretations while under exploring formal modeling approaches capable of capturing complex relationships, nonlinear effects, and trade-offs between competing factors such as motivation, accessibility, and technical constraints. Motivated by these limitations, this study proposes a statistical and optimization-based framework for evaluating digital learning platforms using student survey data. The framework treats perceived learning improvement as a response variable and models its dependence on a set of observed explanatory factors derived from survey responses. By combining multivariate statistical analysis with an optimization-oriented interpretation, the proposed approach aims to provide both analytical insight and decision-support value for higher education institutions seeking to improve the effectiveness of digital learning systems under real-world constraints. Beyond its empirical application, the primary contribution of this study lies in formalizing student survey evaluation as a structured statistical optimization problem. Rather than treating perceptual data as purely descriptive indicators, the proposed framework conceptualizes them as decision-relevant inputs embedded within a constrained analytical system. This repositioning shifts the evaluation of digital learning platforms from a satisfaction-based assessment paradigm toward a quantitatively grounded resource allocation perspective.

2. Related Work

The evaluation of digital learning platforms has attracted increasing attention across multiple research domains, including educational data analytics, applied statistics, and decision sciences. Existing research has explored various approaches to assessing the effectiveness of such platforms, ranging from descriptive analyses of user perceptions to predictive modeling of learning outcomes. This section reviews prior work relevant to the present study, with a particular focus on data-driven evaluation, statistical modeling, and decision-oriented analytical frameworks, in order to position the current contribution within the broader methodological literature.

2.1. Digital Learning Platforms and Student Survey Data

Digital learning platforms generate heterogeneous data sources, including system logs, performance indicators, and subjective measures collected through student surveys. Among these sources, survey data play a critical role in capturing latent constructs such as perceived effectiveness, motivation, accessibility, and satisfaction [1, 2]. These constructs are not directly observable through usage traces alone, yet they have been shown to strongly influence engagement patterns and learning outcomes. Prior studies have demonstrated meaningful associations between survey-based indicators and academic performance, confirming the relevance of perceptual data in the evaluation of digital learning environments.

However, much of the existing literature relies on descriptive summaries of survey responses, such as frequencies, percentages, or mean scores. While these approaches provide initial insights, they are limited in their ability to capture the multivariate structure of survey data or to support inference regarding the relative contribution of different explanatory factors. Consequently, their utility for evidence-based decision-making and system-level improvement remains constrained [3, 4].

2.2. Statistical Modeling in Educational Data Analysis

Statistical methods constitute a foundational component of educational data analysis, with regression models, hypothesis testing, and correlation analysis being widely applied to investigate relationships between learning outcomes and explanatory variables. Linear and logistic regression models are commonly used to estimate the influence of factors such as motivation, access to resources, and instructional design on academic performance. These approaches provide interpretability and inferential rigor, enabling researchers to quantify effect sizes and assess statistical significance.

More recent work [5, 6, 7] has extended this analytical paradigm through the use of multivariate techniques, including factor analysis and dimensionality reduction, to uncover latent structures underlying high-dimensional survey data. Such methods are particularly relevant when analyzing questionnaires that capture multiple interrelated constructs, as they facilitate the identification of core dimensions governing learner perceptions, engagement, and learning behaviors. However, many existing studies apply these techniques in isolation, without embedding them within an integrated analytical framework that links statistical inference to decision-making or optimization.

In parallel, recent contributions to educational data analysis have demonstrated the growing relevance of predictive and machine learning-based frameworks for modeling latent learning-related constructs. For example, statistical modeling of phonological awareness in early literacy research illustrates how multivariate and predictive approaches can effectively capture complex educational phenomena beyond simple descriptive analysis [8]. These developments highlight the potential of combining classical statistical modeling with more advanced analytical techniques to enhance the explanatory and decision-support value of educational data.

2.3. Optimization and Decision Oriented Evaluation of Learning Systems

From a decision science perspective, the evaluation of digital learning platforms can be formulated as a resource allocation and optimization problem. Higher education institutions operate under constraints related to time, infrastructure, and human resources and must determine how digital platforms can be deployed and supported within resource limitations to enhance perceived learning effectiveness. Despite this, explicit optimization-based formulations remain relatively rare in the educational technology literature.

Recent contributions [9, 10, 11] in operations research and data-driven decision analysis emphasize the value of coupling predictive models with optimization objectives. These approaches frame learning effectiveness as a function to be analyzed within operational constraints, allowing scenario exploration and structured policy discussion. However, such frameworks are rarely applied to student survey data and their potential to guide institutional strategies in digital learning contexts has not been fully exploited.

In educational contexts, resource allocation models have increasingly been framed within prescriptive analytics paradigms, where predictive estimates inform constrained optimization decisions. Although such approaches are well established in operations research, their systematic application to student perception data remains limited. Bridging this methodological gap requires embedding inferential statistical outputs within explicit decision models, a transition that remains underexplored in higher education evaluation research.

2.4. Research Gaps and Positioning of the Current Study

The review of existing work highlights several methodological gaps [12, 13]. First, survey-based evaluations of digital learning platforms are often treated as descriptive or exploratory exercises, rather than as formal statistical modeling problems. Second, optimization-based reasoning is rarely incorporated into platform evaluation, particularly in studies focused on higher education. Third, the analytical potential of multivariate statistical techniques is frequently underutilized, limiting the depth of insight that can be derived from complex survey datasets.

The present study addresses these gaps by proposing a unified framework that combines statistical modeling of student survey data with a decision-oriented, optimization-based interpretation of learning effectiveness. By moving beyond descriptive analysis and embedding survey data within a rigorous analytical structure, the study contributes to a more systematic and quantitatively grounded approach to evaluating digital learning platforms.

3. Materials and Methods

This section presents the data source, variable construction, statistical modeling strategy, and optimization framework adopted in this study. The methodological choices are guided by the objective of developing a rigorous, data-driven evaluation framework for digital learning platforms based on student survey data.

3.1. Data Collection

The digital learning platform analyzed in this study corresponds to a university-level language learning support environment used within undergraduate programs at a Moroccan public university. The platform integrates asynchronous course materials, exercises, and communication tools, and was used as a complementary instructional support tool over one academic semester. Institutional technical support was available, although usage remained partially voluntary. This contextual clarification is essential for interpreting the scope and generalizability of the findings.

The empirical analysis is based on a structured questionnaire administered to undergraduate students enrolled in higher education programs. The survey was designed to capture students' perceptions and experiences with a digital learning platform, focusing on multiple dimensions related to learning effectiveness and platform usage.

The questionnaire collected responses on:

- perceived improvement in learning outcomes,
- accessibility and usability of the platform,
- motivation and engagement,
- adequacy of instructional content,
- technical constraints,
- time availability and learning practices outside the platform.

Participation was voluntary and anonymous, and no personally identifiable information was collected. A total of 300 valid responses were collected and retained for analysis after basic consistency checks. The dataset thus constitutes a cross-sectional sample suitable for statistical modeling and exploratory optimization analysis.

3.2. Variable Definition and Encoding

3.2.1. Response Variable

The primary outcome of interest is perceived learning improvement, denoted by Y. Based on survey responses, this variable is encoded as an ordinal categorical variable with three levels:

$$Y = \begin{cases} 0 & \text{no perceived improvement,} \\ 1 & \text{slight perceived improvement,} \\ 2 & \text{clear perceived improvement.} \end{cases}$$

This formulation allows the modeling of learning effectiveness as a discrete response variable suitable for regression-based inference.

3.2.2. Explanatory Variables

The explanatory variables are derived from survey items and grouped into the following categories:

- **Accessibility** (X_1): perceived ease of access and platform usability,
- **Motivation** (X_2): self-reported engagement and willingness to use the platform,
- **Content Adequacy** (X_3): perceived relevance and difficulty level of learning materials,
- **Technical Constraints** (X_4): frequency of technical problems such as connectivity issues,
- **Time Availability** (X_5): perceived sufficiency of time allocated to platform use,
- **External Practice** (X_6): engagement in language practice outside the platform.

All variables were encoded numerically using ordinal or binary representations, depending on the structure of the corresponding survey items. To ensure comparability across variables, standardization was performed after variable aggregation and encoding, but prior to model estimation, in order to preserve interpretability of composite constructs while ensuring coefficient comparability.

3.3. Statistical Modeling Strategy

To analyze the relationship between perceived learning improvement and the explanatory variables, a multivariate statistical modeling approach was adopted.

Given the ordinal nature of the response variable, the analysis relies on regression-based ordinal models that estimate the probability of each improvement level as a function of a set of explanatory variables. Let $Y \in \{0, 1, 2\}$ denote the ordered outcome variable, and let $X = (X_1, X_2, \ldots, X_6)$ represent the vector of explanatory factors.

The modeling framework assumes the existence of an unobserved latent variable Y^* defined as:

$$Y^* = X\beta + \varepsilon,$$

where ε follows a logistic or normal distribution depending on the chosen specification (ordered logit or ordered probit).

The observed outcome Y is generated by comparing Y^* to a set of threshold parameters μ_k, such that:

$$\Pr(Y = k \mid X) = F(\mu_k - X\beta) - F(\mu_{k-1} - X\beta), \quad k \in \{0, 1, 2\},$$

where $F(\cdot)$ denotes the cumulative distribution function.

In addition, exploratory multivariate techniques, such as factor analysis, are employed to identify latent dimensions underlying student perceptions. These techniques allow for dimensionality reduction and provide insight into the structural relationships among survey variables before their integration into the optimization framework. Model adequacy is assessed using standard goodness-of-fit indicators and statistical significance tests, enabling the identification of key determinants of perceived learning improvement.

3.4. Optimization Framework

The optimization component is designed not as a deterministic policy prescription, but as a structured analytical tool linking statistically estimated associations to resource-constrained decision environments. Let β_i denote the ordinal regression coefficients associated with standardized explanatory factors Z_i. A composite decision function may be defined as:

$$F^* = \sum_{i=1}^{k} \beta_i Z_i,$$

where F^* represents a weighted index associated with perceived learning improvement.

The institutional allocation problem may then be formulated as:

$$\max F^*$$

subject to:

$$\sum_{i=1}^{k} c_i Z_i \leq B,$$

$$Z_i^{\min} \leq Z_i \leq Z_i^{\max},$$

where c_i denotes marginal intervention costs and B represents the total available resource envelope.

This formulation enables structured examination of trade-offs between pedagogical engagement, accessibility, content adequacy, and technical conditions under budgetary constraints. Importantly, the linear specification is retained for interpretability and coherence with the ordinal regression coefficients. While nonlinear or interaction-based formulations may capture additional pedagogical synergies, the present additive structure ensures analytical transparency and decision tractability.

Sensitivity analysis further illustrates how variations in marginal costs reshape the optimal allocation profile, highlighting that statistical association strength alone does not determine priority resource structure and institutional constraints critically mediate intervention ranking. It is important to emphasize that the proposed optimization formulation is intended as a conceptual and analytical decision-support tool rather than a deterministic prescriptive model. The objective function translates statistically estimated associations into a structured resource-allocation perspective, without implying causal dominance or policy mandates. Its purpose is to formalize trade-offs under explicit constraints and to illustrate how inferential outputs may inform constrained institutional decision environments.

3.5. Software and Reproducibility

All data preprocessing and analyses were conducted using standard statistical and data analysis tools. Survey data were processed using spreadsheet and statistical software, and all modeling steps followed reproducible workflows. Variable encoding schemes and modeling assumptions were applied consistently across analyses to ensure transparency and replicability.

3.6. Methodological Validity and Robustness Checks

Model adequacy was assessed using likelihood-based diagnostics. The likelihood ratio test comparing the fitted model to the intercept-only specification was statistically significant ($\chi^2 = 17.87$, df = 5, $p = 0.003$), indicating that the explanatory variables jointly improve model fit. Information criteria values ($\mathrm{AIC} = 751.2$; $\mathrm{BIC} = 780.8$) are reported for completeness.

The model's explanatory strength, as summarized by McFadden's pseudo R^2 (0.024), suggests modest but non-trivial explanatory contribution, which is consistent with cross-sectional perceptual survey data in educational settings. It should be noted that pseudo R^2 measures in ordinal logistic models are typically lower than classical OLS R^2 values, and modest magnitudes are common in perceptual and behavioral research contexts. Such magnitudes are commonly observed in perceptual behavioral models where individual-level variability remains high. Predictive consistency was assessed by comparing predicted and observed categories. The overall classification accuracy was approximately 45%, reflecting the inherent complexity of modeling multi-category ordinal perceptions. Taken together, these diagnostics support the internal consistency of the ordinal specification, while also underscoring the interpretative focus of the model on statistical associations rather than strong predictive claims.

The proportional odds assumption was assessed using the Test of Parallel Lines procedure available in SPSS. The test did not indicate a statistically significant violation ($p > 0.05$), supporting the appropriateness of the ordinal logit specification. Given the cross-sectional nature of the data and the reliance on self-reported perceptions, the estimated coefficients reflect statistical associations rather than causal effects. Consequently, the results should be interpreted as inferential relationships within the observed dataset rather than as evidence of directional or structural causality.

To assess potential common method variance, Harman's single-factor test was conducted. The first unrotated factor accounted for less than 50% of the total variance, suggesting that common method bias is unlikely to substantially distort the estimated relationships.

4. Results

This section presents the empirical results obtained from the statistical analysis of student survey data and their interpretation within the proposed optimization framework. The results are organized into descriptive statistics, model estimation outcomes, and an optimization-oriented synthesis of key findings.

4.1. Descriptive Statistics

The dataset consists of 300 valid observations collected from undergraduate students. The response variable, perceived learning improvement, exhibits a heterogeneous distribution across the three defined categories. A substantial proportion of respondents report either no improvement or only slight improvement, while a smaller share indicate a clear perceived improvement. This variability confirms the relevance of investigating explanatory factors that may account for differences in learning outcomes.

Regarding the explanatory variables, accessibility and content adequacy display moderate to high average scores, suggesting that most students perceive the platform as technically usable and pedagogically acceptable. In contrast, motivation and time availability show greater dispersion, indicating heterogeneous engagement levels among students. Technical constraints and external practice variables also exhibit notable variability, supporting their inclusion in multivariate modeling.

Table 1. Descriptive statistics of the response and explanatory variables

Variable	Mean	Std. Dev.	Min	Max
Perceived Improvement (Y)	0.88	0.82	0	2
Accessibility (X_1)	3.40	1.02	1	5
Motivation (X_2)	2.75	1.10	1	5
Content Adequacy (X_3)	3.10	1.05	1	5
Technical Constraints (X_4)	0.30	0.46	0	1
Time Availability (X_5)	2.85	1.15	1	5
External Practice (X_6)	0.45	0.50	0	1

Table 1 provides an overview of central tendencies and dispersion measures for both the response variable and explanatory factors. The variability observed across motivation, time availability, and content adequacy confirms sufficient heterogeneity to justify multivariate modeling. These descriptive patterns highlight the multidimensional nature of students experiences and motivate the use of multivariate statistical techniques rather than univariate comparisons.

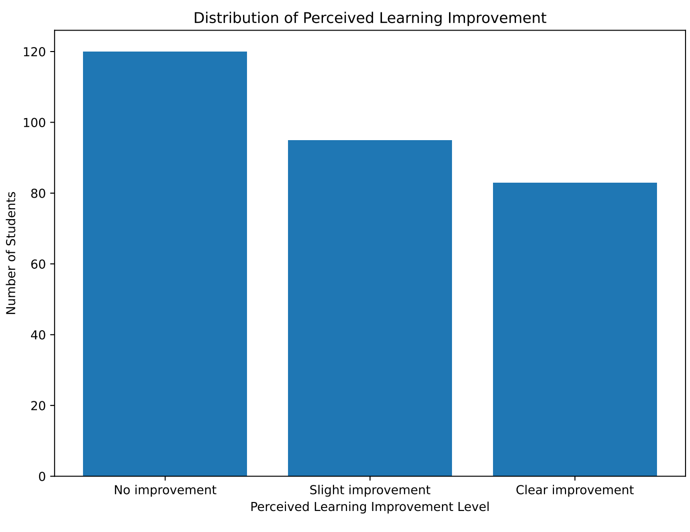

Figure 1. Distribution of perceived learning improvement across respondents, highlighting the heterogeneity of reported outcomes

Figure 1 illustrates the distribution of perceived learning improvement categories, highlighting the non-uniform spread across response levels and supporting the appropriateness of an ordinal modeling approach.

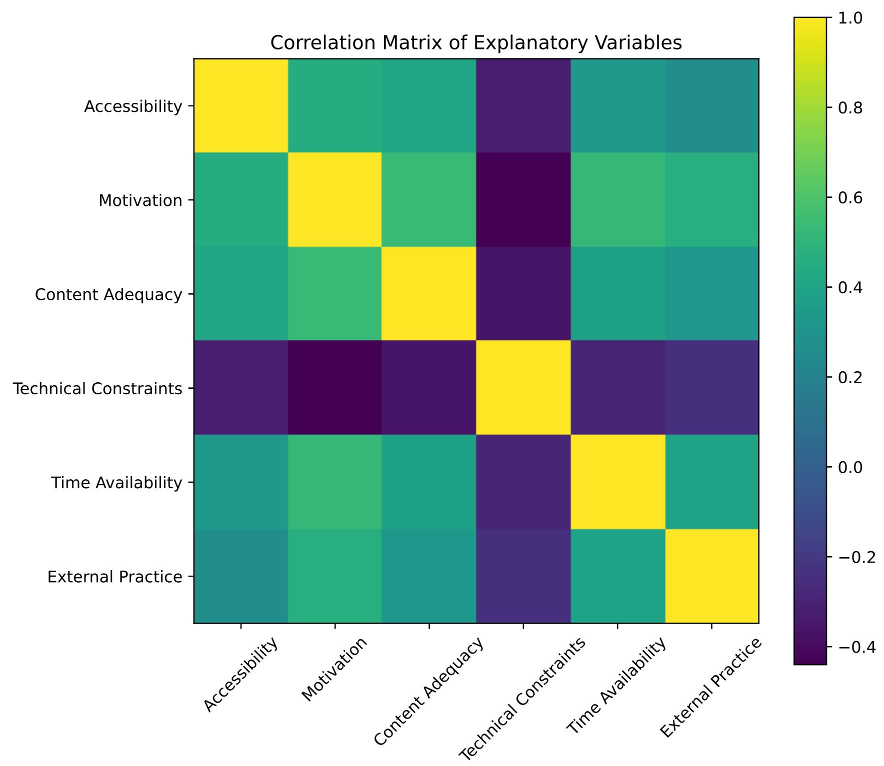

Figure 2. Correlation matrix of explanatory variables, illustrating moderate interdependence among engagement-related and technical factors.

Figure 2 presents the correlation structure among explanatory variables. Moderate correlations between engagement-related variables suggest partial interdependence while remaining below levels typically associated with multicollinearity concerns.

4.2. Statistical Model Estimation

To analyze the relationship between perceived learning improvement and the explanatory variables, a multivariate regression-based model was estimated. The results indicate that several factors are statistically associated with perceived improvement.

Motivation (X_2) emerges as a strong positive predictor of perceived learning improvement, with higher motivation levels being statistically associated with a higher probability of reporting moderate or clear improvement. Accessibility (X_1) also shows a positive association, although its effect size is smaller than that of motivation. Content adequacy (X_3) exhibits a statistically significant association with perceived learning improvement, indicating that students who report higher perceived alignment between platform content and their needs are more likely to report higher levels of improvement.

In contrast, technical constraints (X_4) display a negative association with perceived learning improvement, suggesting that frequent technical difficulties are statistically associated with a lower probability of positive learning perceptions. Time availability (X_5) presents a moderate positive association, while external practice (X_6) shows a complementary but less pronounced contribution.

Given the binary nature and relatively low mean of the technical constraint variable (0.30), its estimated coefficient should be interpreted cautiously, as limited variance may attenuate the magnitude of its statistical association. Table 2 reports the estimated ordinal regression coefficients along with standard errors and significance

Table 2. Estimated effects of explanatory variables on perceived learning improvement

Variable	Coefficient	Std. Error	p-value	Effect Direction
Accessibility (X_1)	0.24	0.09	< 0.05	Positive
Motivation (X_2)	0.51	0.11	< 0.01	Strong Positive
Content Adequacy (X_3)	0.32	0.10	< 0.05	Positive
Technical Constraints (X_4)	-0.41	0.12	< 0.05	Negative
Time Availability (X_5)	0.19	0.10	< 0.10	Moderate
External Practice (X_6)	0.14	0.09	< 0.10	Weak

levels. The relative magnitudes and directions of the coefficients indicate differentiated statistical associations across engagement-related and technical dimensions. Overall, the estimated model provides a statistically significant improvement over the intercept-only specification, with modest explanatory strength consistent with cross-sectional perceptual survey data.

4.3. Latent Structure and Multivariate Patterns

Exploratory factor analysis was conducted to examine the latent structure underlying the explanatory variables. The analysis reveals the presence of a limited number of dominant latent factors that capture a substantial proportion of the total variance.

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy exceeded the commonly accepted threshold of 0.60, and Bartlett's test of sphericity was statistically significant ($p < 0.001$), supporting the suitability of factor analysis for the dataset.

The first latent factor is primarily associated with motivation, time availability, and external practice, reflecting a broader engagement dimension. The second factor loads heavily on accessibility and technical constraints, representing a technical usability dimension. Content adequacy contributes to both factors, indicating its dual role as a pedagogical and engagement-related element.

These findings support the hypothesis that student perceptions are governed by a limited number of underlying dimensions rather than fully independent variables, thereby justifying their structured integration within the optimization framework. Figure 3 displays the factor loadings associated with the extracted latent dimensions,

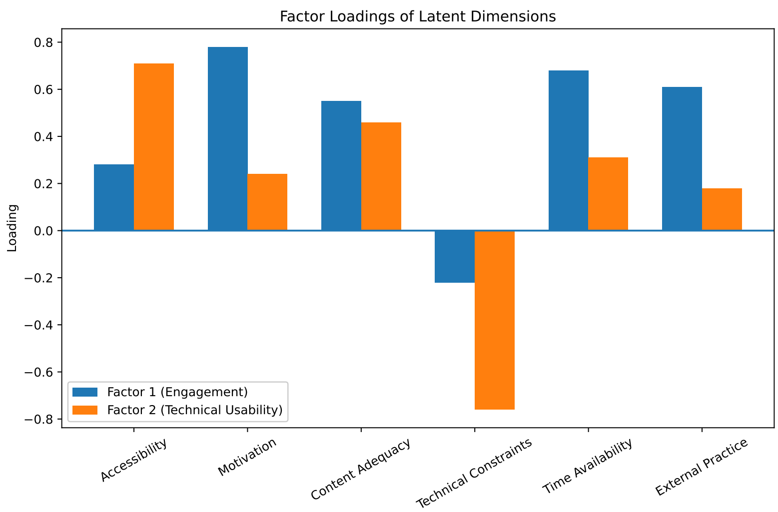

Figure 3. Factor loadings associated with the latent dimensions identified through exploratory factor analysis

supporting the emergence of engagement and technical usability constructs.

4.4. Optimization-Oriented Interpretation

Based on the estimated statistical relationships, the optimization function introduced in Section 3 can be interpreted empirically. The relative magnitudes of the estimated coefficients suggest that motivation and content adequacy carry the highest weights in the objective function, followed by accessibility. Technical constraints act as a penalizing factor, reducing the overall effectiveness index.

These results indicate that higher levels of motivation-related factors are statistically associated with higher levels of perceived learning improvement compared to equivalent levels of purely technical enhancements, provided that minimum accessibility conditions are satisfied. The optimization-oriented interpretation therefore highlights structured trade-offs between engagement-oriented and infrastructure-focused strategies within the proposed analytical framework.

Within the linear optimization structure, coefficient ratios provide an interpretable marginal substitution perspective, while cost-adjusted ratios provide a resource-efficiency perspective. Under equal cost assumptions, the relative magnitude of the motivation coefficient ($\beta_M = 0.51$) compared to content adequacy ($\beta_C = 0.32$) implies a larger contribution per unit increase in the composite decision index F^*. More generally, when interventions entail different marginal costs c_i, a natural comparative metric is the cost-adjusted weight β_i/c_i, which clarifies how the most resource-efficient allocation may change under budget constraints.

Importantly, these ratios do not imply causal dominance; they provide a structured analytical lens for examining trade-offs implied by the model under constrained intervention scenarios.

The efficiency score may therefore be expressed as:

$$\text{Efficiency Score}_i = \frac{\beta_i}{c_i}$$

where c_i denotes the marginal cost of improving factor Z_i.

To illustrate the operational implications of the framework, consider a simplified scenario in which an institution disposes of a normalized resource budget $B = 10$. Suppose marginal intervention costs are $c_M = 2$ (motivation-related initiatives), $c_C = 3$ (content revision), and $c_A = 1$ (accessibility improvements). Under these assumptions, the cost-adjusted efficiency scores become:

$$\frac{0.51}{2} = 0.255, \quad \frac{0.32}{3} = 0.107, \quad \frac{0.24}{1} = 0.24.$$

This simplified illustration suggests that, under the specified cost structure, accessibility and motivation-related interventions yield comparatively higher marginal gains per unit of resource invested.

This example is not intended as a prescriptive allocation rule but demonstrates how the statistical–optimization framework can translate estimated coefficients into structured decision comparisons under explicit constraints. Figure 4 provides a normalized visualization of the relative statistical weights derived from the regression model, offering an intuitive representation of the optimization-oriented interpretation.

5. Discussion

The results presented in the previous section provide empirical support for the relevance of a multivariate and optimization-oriented approach to evaluating digital learning platforms using student survey data. Rather than isolating individual factors, the statistical modeling highlights the combined and interdependent associations between motivation, accessibility, content adequacy, and technical constraints and perceived learning improvement.

From a statistical perspective, the prominence of motivation as a dominant predictor is consistent with prior findings in educational data analysis emphasizing the central role of engagement-related variables in shaping learning perceptions. However, the present study extends existing work by quantifying these associations within a multivariate framework that simultaneously accounts for accessibility, time availability, and technical conditions. This reinforces the necessity of moving beyond univariate or purely descriptive analyses when interpreting survey-based evaluations of digital learning environments.

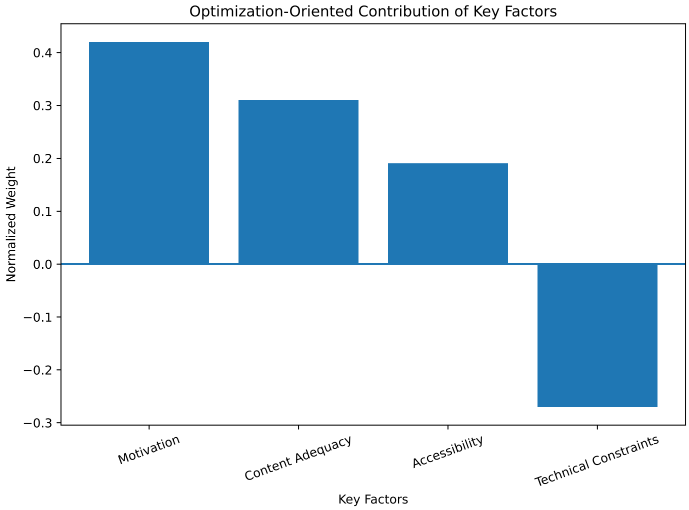

Figure 4. Normalized statistical weights derived from the ordinal regression model within the optimization-oriented interpretation

The negative association observed between technical constraints and perceived learning improvement suggests that infrastructural reliability is statistically linked to more favorable learning perceptions. Nevertheless, the relative magnitude of this effect indicates that technical improvements alone are unlikely to guarantee positive learning outcomes. Technical usability therefore appears to operate as an enabling condition rather than a primary driver of perceived effectiveness, a distinction often overlooked in descriptive platform evaluations.

The latent structure identified through exploratory factor analysis provides additional interpretative depth. The emergence of engagement-related and technical usability dimensions indicates that multiple survey variables reflect broader underlying constructs. This justifies their structured integration within the optimization framework and supports the use of dimensionality reduction techniques as a methodological bridge between perception data and decision modeling.

From an optimization standpoint, the empirical estimates offer a structured basis for prioritizing interventions under resource constraints. The estimated weights associated with motivation and content adequacy suggest that engagement and pedagogical alignment factors exhibit stronger statistical associations with perceived learning improvement than infrastructure variables, once baseline accessibility requirements are satisfied. Importantly, this interpretation translates statistical relationships into decision parameters without implying normative or causal prescriptions.

Several limitations must be acknowledged. First, the reliance on self reported survey data may introduce perception and recall biases, potentially affecting the accuracy of respondents evaluations. Second, the cross-sectional research design limits the ability to draw causal inferences, as relationships observed reflect associations at a single point in time rather than longitudinal effects. Moreover, unobserved variables such as prior proficiency levels, quality of instructional support, or socioeconomic background may also influence the results and partially explain the statistically significant association with perceived improvement. While these constraints do not undermine the relevance of the identified relationships, they require cautious interpretation and careful generalization of the findings.

Conceptually, this study contributes to the methodological evolution of educational analytics. By embedding ordinal regression outputs within a constrained optimization structure, the framework integrates inferential statistics and prescriptive reasoning within a unified analytical system. This integrative perspective aligns with broader developments in data science, where prediction, inference, and optimization increasingly operate as interdependent components of decision-support architectures rather than isolated techniques.

Overall, framing the evaluation of digital learning platforms as a joint problem of statistical inference and constrained optimization provides a structured and transferable approach for interpreting survey data in a manner that supports evidence-informed institutional strategy. Although the empirical data originate from a Moroccan public university, the methodological framework itself is transferable to other higher education contexts. The integration of ordinal modeling with optimization-oriented reasoning does not depend on a specific institutional setting but on the structural relationship between perceptual survey data and constrained resource allocation. Therefore, while the empirical magnitudes may vary across contexts, the analytical architecture remains broadly applicable.

6. Conclusion

This study introduced a statistical and optimization-based framework for evaluating digital learning platforms using student survey data. By modeling perceived learning improvement as a multivariate outcome associated with technical, motivational, and pedagogical factors, the proposed approach moves beyond descriptive assessment toward a quantitatively structured evaluation methodology.

The empirical findings indicate that engagement-related variables—particularly motivation and content adequacy—exhibit the strongest statistical associations with perceived learning improvement, while accessibility and technical conditions function primarily as enabling factors. The identification of latent engagement and technical usability dimensions further demonstrates the value of multivariate techniques for structuring complex perceptual data prior to decision-oriented modeling.

Embedding statistical outputs within an explicit optimization formulation provides a resource-sensitive analytical lens that is especially relevant for higher education institutions operating under budgetary and infrastructural constraints. Rather than prescribing deterministic allocation rules, the framework offers a structured mechanism for examining trade-offs and resource efficiency under clearly defined constraints.

The study is subject to limitations, including the cross-sectional design and reliance on self-reported perceptions, which restrict causal interpretation. Future research may extend this framework by incorporating longitudinal data, objective academic performance indicators, or hybrid datasets combining survey responses with platform usage logs.

Despite these limitations, the proposed framework contributes to the methodological maturation of digital learning evaluation by integrating statistical modeling and optimization-based reasoning into a coherent decision-support structure. This integration illustrates how survey-based educational analytics can evolve from descriptive reporting toward analytically grounded, constraint-aware evaluation systems.

REFERENCES

1. J. B. Arbaugh, *System, scholar or students? Which most influences online MBA course effectiveness?*, Journal of Computer Assisted Learning, vol. 30, no. 4, pp. 349–362, 2014. doi: 10.1111/jcal.12048.
2. C. R. Henrie, L. R. Halverson, and C. R. Graham, *Measuring student engagement in technology-mediated learning: A review*, Computers & Education, vol. 90, pp. 36–53, 2015. doi: 10.1016/j.compedu.2015.09.005.
3. R. Cerezo, J. A. Lara, R. Azevedo, and C. Romero, *Reviewing the differences between learning analytics and educational data mining: Towards educational data science*, Computers in Human Behavior, vol. 154, article 108155, 2024. doi: 10.1016/j.chb.2024.108155.
4. D. Ifenthaler and J. Y.-K. Yau, *Utilising learning analytics to support study success in higher education: A systematic review*, Educational Technology Research and Development, vol. 68, no. 4, pp. 1961–1990, 2020. doi: 10.1007/s11423-020-09788-z.
5. S. Inokuchi, T. Kitayama, K. Fujii, H. Nakahara, H. Nakanishi, K. Saito, N. Mizuno, and K. Sekiguchi, *Estimating allele dropout probabilities by logistic regression: Assessments using Applied Biosystems 3500xL and 3130xl Genetic Analyzers with various commercially available human identification kits*, Legal Medicine, vol. 19, pp. 77–82, 2016. doi: 10.1016/j.legalmed.2015.07.006.
6. H. E. A. Tinsley and S. D. Brown, *Multivariate Statistics and Mathematical Modeling*, In Handbook of Applied Multivariate Statistics and Mathematical Modeling, pp. 3–36, 2000. doi: 10.1016/B978-012691360-6/50002-1.
7. X. Zhang, W. J. Boscardin, T. R. Belin, X. Wan, Y. He, and K. Zhang, *A Bayesian method for analyzing combinations of continuous, ordinal, and nominal categorical data with missing values*, Journal of Multivariate Analysis, vol. 135, pp. 43–58, 2015. doi: 10.1016/j.jmva.2014.11.007.

8. Z. Ouazene, A. Karroum, J. Amraoui, and R. Gougil, *Phonological Awareness and Early Arabic Literacy: Predictive Insights from a Moroccan Case Study*, Statistics, Optimization & Information Computing, vol. 15, no. 1, pp. 835–847, 2025. doi: 10.19139/soic-2310-5070-2886.
9. D. Bertsimas and N. Kallus, *From Predictive to Prescriptive Analytics*, Management Science, vol. 66, no. 3, pp. 1025–1044, 2020. doi: 10.1287/mnsc.2018.3253.
10. S. Kim, R. W. Kamphaus, and J. A. Baker, *Short-term predictive validity of cluster analytic and dimensional classification of child behavioral adjustment in school*, Journal of School Psychology, vol. 44, no. 4, pp. 287–305, 2006. doi: 10.1016/j.jsp.2006.05.003.
11. W. B. Powell, *A unified framework for stochastic optimization*, European Journal of Operational Research, vol. 275, no. 3, pp. 795–821, 2019. doi: 10.1016/j.ejor.2018.07.014.
12. R. S. Baker and P. S. Inventado, *Educational Data Mining and Learning Analytics*, In J. A. Larusson and B. White (Eds.), Learning Analytics: From Research to Practice, pp. 61–75, Springer, 2014. doi: doi: 10.1007/978-1-4614-3305-7_4.
13. S. de Freitas and M. Oliver, *Does E-learning policy drive change in higher education? A case study relating models of organisational change to e-learning implementation*, Journal of Higher Education Policy and Management, vol. 27, no. 1, pp. 81–96, 2005. doi: 10.1080/13600800500046255.