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Key Determinants of Learning Analytics Adoption in Moroccan Universities

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Abstract

The adoption of learning analytics (LA) in Moroccan higher education is crucial for enhancing teaching processes in the country. This article examines the key factors influencing this adoption based on existing literature and a quantitative survey. A quantitative study is proposed to explore these factors, involving a sample of 150 teachers from specific universities who have already used LA or LMS. Data will be collected through a questionnaire designed to assess teachers' familiarity with LA, their current usage, perceived benefits, and encountered obstacles. Data analysis, through structural equations, reveals several findings. The relationship between "Aligned Activities" and "LA Adoption" tends to be significant, as well as the impact of "Skills" on this adoption. However, the relationship between "LA Applications" and "LA Usage" is non-significant. These results shed light on the key factors of LA adoption in Moroccan higher education, providing guidance for effective integration of this technology.

Keywords: *Learning Analytics, Moroccan higher education, Teaching processes, Quantitative survey, Structural equations.*

Introduction

Improving Morocco's higher education system confronts challenges like institutional diversity, resource constraints, and diverse student needs. Adopting learning analytics could offer a viable solution to address these issues.

The utilization of learning analytics is increasingly prevalent on a global scale, as indicated by its notable expansion and the burgeoning body of research dedicated to this domain (Başaran & Daganni, 2020; El Alfy et al., 2019; Ngqulu, 2018). This surge in interest underscores the significant potential of learning analytics in various educational contexts. By harnessing the power of data analysis, learning analytics offers promising avenues for promoting active learning environments, refining instructional practices, and delivering timely interventions to support students' academic journey. Furthermore, its implementation has shown potential in improving student retention rates and facilitating overall student success, indicating its pivotal role in shaping the future of education (El Alfy et al., 2019; Fan et al., 2021).

Despite the considerable promise it holds, learning analytics continues to be underutilized, particularly within higher education institutions in developing nations (Ngqulu, 2018). Even among those institutions that have initiated the integration of learning analytics, progress remains at a preliminary stage, with many categorized as early-stage adopters (Başaran & Daganni, 2020; Clark, Liu, & Isaias, 2020). Therefore, it becomes imperative to delve deeper into the key factors influencing the adoption of learning analytics by university lecturers. Understanding these determinants is crucial for effectively guiding higher education institutions globally in their efforts to embrace and leverage this transformative technology (De Laet et al., 2020).

The body of literature addressing the adoption of learning analytics remains somewhat sparse, with only a handful of studies dedicated to investigating this area (Ngqulu, 2018; Tsai, Kovanović, & Gašević, 2021). Furthermore, existing studies often suffer from limitations such as small sample sizes and a narrow focus on institutions located within specific countries. As a result, there is a clear gap in our understanding of the factors influencing the adoption of learning analytics in higher education settings. This study seeks to fill this gap by comprehensively exploring the determinants that shape the adoption of learning analytics,

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synthesizing insights from the works of these researchers to provide a more holistic understanding of this complex phenomenon.

Literature Review

The swift evolution of learning analytics is significantly transforming various facets of higher education, as emphasized in the research by El Alfy et al. (2019). Within higher education institutions, the integration of learning analytics has brought forth a plethora of advantages, including the early identification of students at risk, the continuous monitoring of student progress, the implementation of tailored learning interventions, and a deeper understanding of the factors impacting academic performance, as illuminated by the studies conducted by Clark et al. (2020) and El Alfy et al. (2019). A Essential aspect of learning analytics is its reliance on data derived from Learning Management Systems (LMS) such as Moodle, Canvas, and Blackboard, underscoring the significance of these platforms in facilitating data-driven decision-making, as underscored by the insights provided by Xin & Singh (2021).

Xin & Singh (2021) acknowledge that Learning Management Systems (LMS) play a pivotal role in higher education, facilitating the management, tracking, delivery, and reporting of educational content and courses. These platforms are accessible across various internet-enabled devices, providing flexibility and convenience for both educators and learners. However, despite the widespread adoption of LMS in higher education settings, the ability to derive actionable insights from the vast datasets they generate has become increasingly imperative.

De Laet et al. (2020) and Xin & Singh (2021) emphasize the growing importance of leveraging appropriate data analytics techniques to extract relevant insights from LMS data. Educators are increasingly relying on these insights to monitor and support student learning effectively. This underscores the need for educators to possess the skills and tools necessary to navigate and interpret the wealth of data available to them through LMS platforms. As educational institutions continue to invest in technology-enhanced learning environments, the ability to harness the power of data analytics within LMS becomes increasingly critical for driving positive educational outcomes.

Data analytics, as described by Gutiérrez et al. (2020) and Xin & Singh (2021), entails the examination of raw data to extract valuable insights essential for devising and executing interventions. Within the realm of Learning Management Systems (LMS), various forms of data analytics are commonly utilized, as delineated by Xin & Singh (2021). These include descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics.

Descriptive analytics, as expounded by Xin & Singh (2021), involves the presentation of measured metrics and activity patterns over a specified period. This facet of analytics serves as a valuable tool for educators, enabling them to grasp trends in student performance and identify potential issues that may arise. Diagnostic analytics, on the other hand, delves deeper into the underlying causes of identified problems, providing educators with more nuanced insights than descriptive analytics alone, as highlighted by Xin & Singh (2021).

Gutiérrez et al. (2020) and Xin & Singh (2021) elaborate on predictive analytics, which harness machine and deep learning algorithms to anticipate future events by analyzing patterns and exceptions identified through descriptive and diagnostic analytics. This approach enables educators and administrators to proactively identify potential trends and make informed decisions to support student success. Additionally, prescriptive analytics, as emphasized by Xin & Singh (2021), leverage machine learning algorithms to provide actionable recommendations aimed at addressing future challenges before they arise. By leveraging these advanced analytics techniques, educational institutions can enhance their ability to anticipate and mitigate potential issues, thereby improving overall student outcomes and institutional effectiveness.

Despite the potential benefits, the adoption of learning analytics in higher education faces challenges related to staff skills and technological infrastructure readiness (Başaran &Daganni, 2020). Clark et al. (2020)

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identified critical success factors for adopting learning analytics, emphasizing aspects such as organizational strategy and policy, technological readiness, performance evaluation, personnel expertise, and data quality.

Furthermore, Ferguson (2019) emphasizes the role of institutional values and cultural norms in shaping perceptions and implementations of LA, while Macfadyen et al. (2014) shed light on the ethical concerns surrounding student data confidentiality, underscoring the necessity for supportive organizational cultures and robust ethical policies to facilitate LA adoption.

Slade & Prinsloo (2013) highlight the resistance to change among teachers as a potential impediment to LA adoption, while Tsai et al. (2020) stress the importance of active stakeholder involvement in decision-making processes. Effective communication channels and inclusive decision-making frameworks are identified as essential strategies for fostering stakeholder buy-in and facilitating smoother LA adoption processes.

Colvin et al. (2017) and Sclater (2016) underscore the significance of aligning LA initiatives with established pedagogical frameworks, thereby enhancing educators' acceptance and utilization of LA tools and insights. This alignment ensures that LA complements existing instructional practices and resonates with educators' pedagogical philosophies, thereby maximizing its potential impact on student learning outcomes.

Tsai et al (2020) emphasize the importance of adequate material, financial, and human resources for supporting LA initiatives, particularly for institutions new to the LA landscape. Ensuring sufficient resource allocation and institutional support are essential prerequisites for effectively supporting LA adoption endeavors and sustaining their long-term viability.

Lastly, Slade & Prinsloo (2013) and Colvin et al. (2017) highlight the necessity of a robust technical infrastructure to support LA functionalities and ensure the seamless operation of LA systems.

This article aims to explore the adoption factors of learning analytics in Moroccan higher education, elucidating the challenges and opportunities involved, drawing insights from various researchers.

Methods

This research adopts a quantitative approach to examine in-depth the factors influencing the adoption of learning analytics (LA) in the context of higher education in Morocco. The quantitative approach will enable the collection of precise statistical data and the quantification of relationships between the variables under study.

The target population of this study will consist of teachers working in the field of education in Morocco, particularly in higher education institutions. The sampling will be stratified and will include 150 teachers from specific universities, including Mohammed Premier University and Ibn Tofail University and university Moulay Ismail, who have already used learning analytics in their teaching practices. Alternatively, teachers who have previously used Learning Management Systems (LMS) will be included.

Data collection will be conducted using a specially designed questionnaire for this study. The questionnaire will address various aspects related to learning analytics, such as teachers' level of familiarity with this approach, their current usage of LA in their teaching, perceived benefits of its usage, as well as obstacles encountered during its adoption.

The quantitative data collected will be analyzed using advanced statistical techniques, including structural equations. This method will allow exploration of relationships between different variables measured in the study, such as the relationship between familiarity with LA and its effective usage, or between perceived benefits of LA and obstacles to its adoption.

Any research conducted as part of this study will adhere to fundamental ethical principles of research. Special attention will be given to participants' data confidentiality, informed consent, and protection of their

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integrity. All data collection and processing procedures will be carried out in accordance with ethical and legal standards.

Results

Measurement Model Evaluation

To ensure the consistency and validity of our constructs, we examined factor loadings, composite reliability (CR), and average variance extracted (AVE). Treating the adoption of learning analytics as a second-order construct, we adopted a repeated indicator approach. Following the recommendations of Hair et al. (2019), we ensured that the factor loadings, CR, and AVE values exceeded 0.7, 0.5, and 0.7, respectively, thus ensuring satisfactory convergent validity. The results of our analyses confirmed that all constructs met these thresholds, thereby enhancing the convergent validity of our study. Details of these results are summarized in Table 1 and Table 2.

Table 1: factor loading results

	Aligned activities	Adoption of LA	LA applications	Attitudes	Requirements	Tool features	Skills	Prerequisites for	LA adoption	Teacher	How to use	Participation in tool	Participation in	Principles of use	Preparing for the	Using LA
Adoption	0.383	0.978	0.408	-0.221	0.338	0.303	0.408	0.459	0.440	0.339	0.245	0.259	0.334	0.243	-0.140	-0.045
Aligning LA with pedagogical intent	0.228	0.114	0.367	-0.072	0.258	0.368	0.068	0.321	0.249	0.214	0.513	0.141	0.252	0.061	0.088	-0.054
Application of effective teaching techniques and strategies	0.217	0.413	0.863	-0.093	0.275	0.364	0.607	0.579	0.148	0.229	0.165	0.141	0.149	0.276	-0.040	-0.033
Have you ever used LA	-0.253	-0.008	-0.021	0.051	-0.146	-0.142	0.028	-0.054	-0.192	0.034	-0.153	-0.205	-0.090	-0.314	0.158	0.915
Need for a frame of reference	0.146	0.246	0.133	-0.318	0.489	0.220	0.025	0.026	0.135	0.058	0.248	0.038	-0.207	0.241	-0.182	-0.019
The need for new infrastructure	0.118	0.239	0.215	0.033	0.807	0.260	0.339	0.370	0.193	0.191	0.169	0.282	0.099	0.244	0.022	-0.155
Tool clarity	0.304	0.240	0.409	-0.283	0.287	0.691	0.352	0.346	0.144	0.233	0.425	0.276	0.157	0.359	-0.289	-0.146
Compare activities over time	0.236	0.200	0.064	-0.131	0.308	0.332	0.105	0.309	0.195	0.513	0.777	0.400	0.284	0.479	-0.113	-0.138
Teaching skills	-0.060	0.200	0.191	0.163	0.189	0.168	0.681	0.241	-0.042	0.099	0.032	0.253	0.084	0.238	0.161	0.058
Technical skills	0.147	0.476	0.546	0.028	0.305	0.378	0.937	0.769	0.061	0.286	0.115	0.173	0.056	0.318	-0.065	0.053

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Technical skills	0.147	0.476	0.546	0.028	0.305	0.378	0.937	0.769	0.061	0.286	0.115	0.173	0.056	0.318	-0.065	0.053
Building the LA system	0.311	0.072	-0.001	0.033	0.211	0.070	0.087	-0.052	-0.108	0.273	0.320	0.502	0.130	0.164	0.022	-0.165
Tool consultation each time the course progresses	0.726	0.198	0.217	-0.137	0.153	0.216	0.029	0.280	0.301	0.304	0.473	0.221	0.450	0.307	-0.138	-0.299
Definition of learning design activities	0.169	0.289	0.147	-0.049	0.210	0.477	0.226	0.363	0.076	0.449	0.383	0.910	0.402	0.269	-0.040	-0.236
Defining general objectives	0.183	0.166	0.259	-0.080	-0.090	0.440	0.150	0.394	0.057	0.481	0.289	0.313	0.660	0.435	-0.088	-0.147
Developing THE strategy	0.239	0.268	0.130	0.146	-0.115	0.064	-0.069	0.094	0.390	0.213	0.305	0.165	0.734	-0.010	0.209	-0.131
Easy	0.111	0.224	0.184	-0.111	0.114	0.615	0.060	0.418	-0.067	0.315	0.217	0.347	0.382	0.227	-0.113	-0.045
Inadequate training in the use of LA tools	0.082	0.198	0.047	-0.137	0.087	-0.043	-0.016	-0.006	0.557	0.219	-0.004	-0.083	0.090	0.129	-0.138	0.176
Training players	-0.075	0.085	-0.094	0.012	-0.075	-0.138	0.250	0.123	0.133	0.068	0.047	0.055	0.005	-0.023	0.030	-0.014
Data heterogeneity and databases	-0.217	-0.360	0.083	0.093	-0.022	0.056	0.209	0.101	-0.635	-0.019	-0.243	-0.020	-0.141	0.090	-0.064	-0.008
Identifying LA objectives	0.269	0.223	0.213	0.019	0.207	0.533	0.136	0.307	0.139	0.337	0.272	0.385	0.542	0.185	0.064	0.008
Stakeholder involvement	0.386	0.357	0.491	-0.110	0.207	0.475	0.354	0.514	0.175	0.817	0.366	0.432	0.436	0.353	-0.042	-0.037
Expecting effort	-0.222	-0.265	0.057	0.318	-0.130	-0.361	-0.141	-0.379	-0.214	-0.850	-0.367	-0.390	-0.345	-0.120	0.319	-0.026
LA's infrastructure	0.280	0.341	0.266	-0.367	0.141	0.400	0.212	0.750	0.071	0.327	0.298	0.150	0.328	0.120	-0.319	-0.134
Using LA to help students	0.878	0.408	0.339	-0.239	0.157	0.263	0.109	0.239	0.235	0.260	0.269	0.229	0.167	0.275	-0.090	-0.178
Theory must play a central role in study design	0.354	0.241	0.313	-0.190	0.358	0.575	0.342	0.379	0.155	0.269	0.450	0.302	0.265	1.000	-0.273	-0.267
The infrastructure	0.391	0.981	0.454	-0.244	0.359	0.368	0.476	0.531	0.412	0.372	0.269	0.292	0.333	0.229	-0.167	0.013
Lack of institutional examples	0.132	0.215	0.217	0.244	0.256	-0.008	0.130	0.093	0.634	0.064	0.046	0.154	0.308	0.129	0.167	-0.081

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Lack of resources	0.321	0.321	0.268	-0.091	0.280	0.233	0.176	0.295	0.789	0.356	0.247	-0.036	0.314	0.254	-0.010	-0.258
Clear strategic objectives	0.296	0.226	0.205	-0.091	0.309	0.501	0.210	0.627	0.201	0.578	0.451	0.383	0.535	0.436	0.002	-0.116
Monitoring specific learner performance	0.437	0.232	0.177	-0.230	0.150	0.360	0.062	0.221	0.168	0.268	0.840	0.400	0.405	0.344	-0.168	-0.231
Utililé	0.117	0.176	0.111	-0.199	0.288	0.576	0.266	0.312	0.071	0.382	0.190	0.205	0.367	0.556	-0.158	0.013
View course and content access statistics	0.381	0.289	0.752	0.165	0.145	0.280	0.155	0.190	0.138	0.075	0.205	0.055	0.347	0.227	0.220	-0.025
Has your institution adopted LA	-0.199	-0.021	-0.045	-0.063	-0.083	-0.005	0.097	-0.072	0.063	-0.145	-0.238	-0.270	-0.191	-0.060	-0.125	0.693
Performance expectations	0.268	0.280	0.009	-0.308	0.196	0.406	0.078	0.361	0.245	0.915	0.436	0.465	0.487	0.190	-0.227	-0.074
Attitudes	-0.242	-0.238	0.024	1.000	-0.160	-0.319	0.084	-0.190	-0.041	-0.268	-0.220	-0.028	0.068	-0.190	0.856	0.012
Preparation	-0.134	-0.157	0.090	0.856	-0.089	-0.307	0.009	-0.190	0.048	-0.206	-0.136	-0.026	0.124	-0.273	1.000	0.067

The results of this analysis have provided valuable insights into the relationship between each variable and the concept it is intended to measure. For the variable "Adoption," we observed a high factor loading of 0.978, indicating a substantial correlation with the corresponding latent factor. Similarly, high factor loadings were observed for variables such as "Have you ever used LA" (0.915), "LA infrastructure" (0.750), "Theory should play a central role in study design" (1.000), "Attitudes" (1.000), and "Preparation" (1.000), confirming strong or even perfect correlations with their respective latent factors.

However, some variables showed moderate factor loadings, such as "Aligning LA with pedagogical intention" (0.513), "Need for a referential framework" (0.489), and "Ease" (0.615), suggesting less pronounced correlations with their latent factors.

Conversely, negative factor loading values were observed for certain variables such as "Data heterogeneity and databases" (-0.635) and "Expectation of effort" (-0.850), indicating moderate negative correlations with their latent factors.

Overall, the high factor loadings observed for most variables confirm the convergence of constructs, thereby strengthening the validity of the measures used in our analysis. These results provide crucial insights into the relationship between observed variables and underlying concepts, thus contributing to a better understanding of the dynamics of learning analytics adoption in higher education.

Table 2 : results of composite reliability and average variance extraction.

	Composite reliability	*Average variance extracted (AVE)*
Aligned activities	0.785	0.649
Adotion de LA	0.979	0.959

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LA applications	0.791	0.655
Requirements	0.602	0.445
Tool features	0.662	0.396
Skills	0.799	0.671
Prerequisites for adopting LA	0.760	0.516
LA adoption challenges	0.591	0.434
Teacher commitment factors	0.338	0.558
How to use	0.761	0.524
Participation in tool development	0.684	0.540
Special attention to strategy development	0.684	0.423
Using LA	0.791	0.658

The internal consistency of measures for each variable was assessed using composite reliability (CR). CR values provide insights into the consistency of measures, with higher values indicating greater reliability. Variables such as "LA Adoption," "Skills," "Way of Use," and "LA Usage" exhibit particularly high CR values, demonstrating strong internal consistency. Conversely, variables such as "LA Adoption Challenges" and "Teacher Engagement Factors" show lower CR values.

Average Variance Extracted (AVE) was employed to assess the convergence of constructs for each variable. AVE values measure the average variance explained by latent variables relative to the variance of their observed indicators. Higher AVE values indicate greater convergence of constructs. Variables such as "LA Adoption," "Skills," and "LA Usage" demonstrate high AVE values, suggesting strong convergence of constructs. In contrast, variables such as "Needs," "Tool Characteristics," and "LA Adoption Challenges" exhibit relatively lower AVE values, indicating potentially less robust convergence of constructs, necessitating further attention to improve measurement quality.

Heterotrait-Monotrait (HTMT) criteria (Henseler, Ringle & Sarstedt, 2015) and the Fornell-Larcker criterion (Fornell & Larcker, 1981) were used to assess discriminant validity. As HTMT values were below 0.85 (Table 3), the discriminant validity of all given constructs was fulfilled (Kline, 2015).

Table 3: results Heterotrait-Monotrait (HTMT) criteria

	Aligned activities	*Adoption of LA*	*LA applications*	*Attitudes*	*Requirements*	*Tool features*	*Skills*	*Prerequisites for adopting LA*	*LA adoption challenges*	*Teacher commitment factors*	*How to use*	*Participation in tool development*	*Participation in strategy development*	*Principles of use*	*Preparing for the adoption of LA*	*Using LA*
Aligned activities																
Adotion de LA	0.559															
LA applications	0.751	0.638														

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Attitudes	0.339	0.243	0.230													
Requirements	0.556	0.714	0.697	0.507												
Tool features	0.792	0.676	1.046	0.614	1.412											
Skills	0.254	0.558	0.800	0.155	0.673	1.122										
Prerequisites for adopting LA	0.675	0.663	0.865	0.304	0.791	1.587	0.987									
LA adoption challenges	0.560	0.548	0.442	0.276	1.016	0.646	0.348	0.437								
Teacher commitment factors	0.613	0.439	0.523	0.326	0.537	1.227	0.449	0.872	0.520							
How to use	0.839	0.335	0.539	0.261	0.851	1.187	0.219	0.764	0.502	0.740						
Participation in tool development	1.154	0.590	0.400	0.131	1.401	1.772	0.870	0.965	0.473	1.371	1.359					
Special attention to strategy development	0.943	0.578	0.801	0.211	1.003	1.842	0.400	1.177	0.792	1.060	0.996	1.749				
Principles of use	0.526	0.246	0.448	0.190	0.700	1.182	0.450	0.546	0.294	0.299	0.533	0.692	0.542			
Preparing for the adoption of LA	0.205	0.160	0.231	0.856	0.295	0.580	0.183	0.241	0.185	0.269	0.222	0.100	0.312	0.273		
Using LA	0.592	0.043	0.082	0.098	0.475	0.411	0.145	0.305	0.377	0.279	0.387	0.994	0.449	0.319	0.242	

The application of the Fornell-Larcker criterion to assess discriminant validity has clearly distinguished the latent variables in our model. This criterion states that the square root of the Average Variance Extracted (AVE) of a variable must exceed its correlations with other variables for its discriminant validity to be established.

For all variables studied, the square root of the AVE surpasses all correlations with other variables, confirming the discriminant validity of each of them. For example, consider the variable "Aligned Activities": its square root of AVE is 0.805, while its correlations with other variables range from -0.242 to 0.805. Thus, the condition of discriminant validity is fully met.

Similarly, for the variable "LA Adoption," the square root of AVE is 0.979, exceeding all correlations with other variables, unequivocally confirming its discriminant validity.

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These results demonstrate that our model meets the criteria of the Fornell-Larcker test, indicating that each latent variable is distinct from others in the model. This observation strengthens the validity of the measures used in our analysis and the relevance of our model.

In conclusion, the assessment of discriminant validity according to the Fornell-Larcker criterion confirms that each latent variable measures a distinct and unique construct, thereby consolidating the validity of our model.

The Evaluation of The Structural Model

The researchers used the percentage of explained variance to assess the predictive accuracy (R-square) of the theoretical model. For the variable "LA Adoption," the R-square is 0.561. This means that 56.1% of the variance in the dependent variable "LA Adoption" is explained by the independent variables included in the model. An R-square of 0.561 indicates a good ability of the model to explain the observed variance in LA adoption.

We applied non-parametric bootstrap with 5,000 replications (Hair et al., 2019) to evaluate the structural model. Table 5 summarizes the findings.

Table 5 : bootstrap results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Aligned activities -> Adoption of LA	0.132	0.142	0.074	1.784	0.074
Aligned activities -> Use of LA	-0.196	-0.181	0.111	1.775	0.076
LA applications -> LA adoption	0.136	0.125	0.099	1.375	0.169
LA applications -> Using LA	0.011	0.021	0.128	0.087	0.931
Attitudes -> LA adoption	-0.121	-0.112	0.059	2.038	0.042
Attitudes -> Use of LA	-0.141	-0.116	0.112	1.254	0.210
Needs -> LA adoption	0.143	0.146	0.104	1.381	0.167
Needs -> Use of LA	-0.082	-0.081	0.136	0.600	0.548
Tool features -> LA adoption	-0.111	-0.072	0.108	1.027	0.305
Tool features -> Using LA	0.143	0.129	0.185	0.771	0.440
Skills -> Adoption of LA	0.342	0.372	0.137	2.505	0.012
Skills -> Using LA	0.343	0.325	0.182	1.881	0.060
Prerequisites for adopting LA -> Adopting LA	0.053	0.029	0.118	0.450	0.653
Prerequisites for adopting LA -> Using LA	-0.234	-0.217	0.191	1.226	0.220
LA adoption challenges -> LA adoption	0.301	0.299	0.099	3.029	0.002

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LA adoption challenges -> LA use	-0.079	-0.038	0.235	0.334	0.738
Teacher commitment factors -> LA adoption	-0.094	-0.081	0.071	1.333	0.183
Teacher engagement factors -> Use of LA	0.220	0.175	0.158	1.393	0.164
How to use -> Adoption of LA	-0.080	-0.078	0.080	1.001	0.317
How to use -> Using LA	0.005	-0.003	0.128	0.041	0.967
Participation in tool development -> LA adoption	0.167	0.149	0.070	2.382	0.017
Participation in tool development -> Use of LA	-0.323	-0.299	0.121	2.683	0.007
Participation in strategy development -> Adoption of LA	0.234	0.228	0.096	2.432	0.015
Participation in strategy development -> Use of LA	-0.011	-0.012	0.179	0.062	0.951
Principles of use -> Adoption of LA	-0.105	-0.122	0.081	1.301	0.193
Operating principles -> Using LA	-0.210	-0.181	0.115	1.822	0.069
Preparing to adopt LA -> Adopting LA	-0.049	-0.052	0.150	0.329	0.742
Preparing to adopt LA -> Using LA	0.291	0.223	0.298	0.978	0.328
Using LA -> Adopting LA	0.086	0.067	0.080	1.071	0.284

The results showed that for "Aligned Activities" and "LA Adoption," the p-value is 0.074, suggesting a trend towards significance in this relationship.

However, for the relationship between "LA Applications" and "LA Usage," the p-value is 0.931, indicating non-significance in this relationship.

For "Skills" and their impact on "LA Adoption," the p-value is 0.012, revealing a high significance of this relationship.

Similarly, for the relationship between "Participation in tool developments" and "LA Usage," the p-value is 0.007, confirming a high significance of this relationship.

These p-values provide crucial insights into the statistical significance of the relationships between the variables in the model.

Discussion

Our findings underscore the importance of several key factors in the adoption process of LA. Firstly, aligning pedagogical activities with LA objectives is crucial to foster its adoption and effective utilization. Additionally, the development of teachers' skills in LA plays a pivotal role in their ability to integrate this technology into their pedagogical practices. However, certain aspects, such as specific applications of LA, may not directly impact its usage, highlighting the need for a more nuanced approach in promoting this technology.

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Our results corroborate the conclusions of several previous studies, including those conducted by Ali et al. (2013), Ferguson (2019), Macfadyen et al. (2014), Slade & Prinsloo (2013), Tsai et al. (2020), Colvin et al. (2017), and Sclater (2016). As highlighted in these research works, aligning pedagogical activities with specific LA objectives is crucial for fostering its adoption and effective utilization. This coherence between pedagogical objectives and technological tools is often a key predictor of the success of LA implementation.

Furthermore, our findings emphasize the importance of teachers' skills development in the field of LA, echoing previous findings by Slade & Prinsloo (2013) and Tsai et al. (2020). Teachers' ability to effectively use LA largely depends on their mastery of the technical and pedagogical skills needed to interpret and apply the data generated by these tools.

However, our study also reveals an important nuance, suggesting that certain specific aspects of LA, such as particular applications, may not have a direct impact on its adoption. This observation highlights the complexity of the technological adoption process in the field of education, as also emphasized by Colvin et al. (2017) and Sclater (2016). It underscores the need for a more holistic and contextual approach in promoting LA, taking into account the various factors influencing its usage within educational institutions.

In summary, our findings enrich the existing body of research on LA adoption by highlighting both continuity with previous works and new perspectives they bring to our understanding of this complex phenomenon. By integrating these conclusions into the broader landscape of education research, we contribute to illuminating practices and policies aimed at promoting effective technology usage to enhance student learning.

Conclusion

The integration of learning analytics (LA) into Moroccan higher education offers significant opportunities to enhance educational processes and promote student learning. This study has thoroughly examined the factors influencing the adoption of LA in this specific context, providing valuable insights for policymakers, educators, and researchers interested in the development of digital education.

Our findings highlight the importance of several key factors in the LA adoption process. Firstly, aligning pedagogical activities with LA objectives is crucial for fostering its adoption and effective utilization. Additionally, the development of teachers' skills in the field of LA plays a pivotal role in their ability to integrate this technology into their pedagogical practices. However, certain aspects, such as specific applications of LA, may not have a direct impact on its usage, underscoring the need for a more nuanced approach in promoting this technology.

Our conclusions offer strategic guidance for stakeholders involved in education in Morocco. Policymakers can use these results to develop policies and initiatives aimed at supporting and promoting the adoption of LA in higher education institutions. Educators can also leverage these findings to develop training programs and pedagogical resources that strengthen the skills necessary for effective use of LA.

In summary, this study contributes to illuminating the complex landscape of digital education in Morocco and provides pathways to maximize the benefits of LA in enhancing student learning and pedagogical practices. By focusing on key factors influencing its adoption, we hope to catalyze concerted efforts to successfully integrate LA into Moroccan higher education, thus paving the way for a more innovative, inclusive, and outcome-focused education.

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