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From Institutional Provision to Student Adoption: Digital Language Learning behavioral intention of Use in a Moroccan Higher Education

Sarah JUIDETTE, ***(Lecturer-researcher)***
Laboratory for prospective research in economics and management LRPEG
ENCG Casablanca
Hassan II University Casablanca, Morocco

Asmaa ZRAIOUIL, ***(Doctoral student monitor)***
Laboratory for prospective research in economics and management LRPEG
ENCG Casablanca
Hassan II University Casablanca, Morocco

Nadia CHAFIQ, ***(Lecturer-researcher)***
Department of Communication Sciences and Humanities
Ben M'Sick Faculty of Sciences
Hassan II University Casablanca, Morocco

Correspondence address:	ENCG Casablanca Beau site, B.P 2725 Ain Sebaâ, Casablanca Maroc contact@encgcasa.ma (+212) 5 22 66 08 52
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From Institutional Provision to Student Adoption: Digital Language Learning Use in a Moroccan Higher Education

Abstract:

The sociolinguistic dynamic in Morocco presents a major challenge inviting national institutions to propose educational solutions in order to guarantee equal opportunities for students. On the other hand, higher education is experiencing a mass demand, digital learning is considered as a solution for quality learning (Boumahdi 2021). In this context, and following the progress of modernization and pedagogical innovation; the Ministry of Higher Education and Scientific Research has launched an ambitious project called Pacte Esri (The National Strategy for Accelerating the Transformation of Higher Education, Scientific Research, and Innovation System), in which the ministry signed a contract with the language platform Rosetta stone with the objective of foreign language learning for all Moroccan students in higher education.

The main aim of this study is to evaluate the experience of students involved in required training on the Rosetta Stone platform and explore their intention to use and more specifically to investigate the transition from the institutional provision to the adoption of the platform. Our study is based on a quantitative cross-sectional approach with a sample of 1548 in which data was collected over a single period in order to explore our research question through the lens of our hypotheses. These hypotheses are based on the revised UTAUT2 model, which uses the following variables: performance expectations, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived value, habit by adding an additional variable which is the course of the exam process, and behavioral intention as the dependent variable. The results of the analysis of the main components allowed us to examine the various factors that can influence the behavior intention of the Rosetta platform. The regression analysis with robust standard errors corrected using the HC3 method confirmed that hypotheses: performance expectations (coefficient = 0.065, p-value = 0.0112), facilitating conditions (coefficient = 0.1, p-value = 0), hedonic motivation (coefficient = 0.065, p-value = 0.0112), habits (coefficient = 0.416, p-value = 0) and the exam process (coefficient = 0.158, p-value = 0) greatly influence the actual use of the platform. Social influence (coefficient = 0.041, p-value = 0.06) was marginally validated, while effort expectations (coefficient = 0.005, p-value = 0.859) and perceived value (coefficient = 0.026, p-value = 0.226) were not confirmed.

Following these findings, it is recommended that educational departments capitalize on the integration of the platform into the formal exam process given its importance as a determining factor in usage. To optimize this experience, institutions should empower facilitating conditions by resolving technical issues and providing comprehensive documentation at the beginning of each module. Supporting habit formation and fostering hedonic motivation, policymakers can ensure students fully benefit from the potential of this modern digital tool, thereby maximizing the impact of the learning pedagogical innovations.

Keywords: Digital learning, Languages, user experience, UTAUT2.
JEL Classification: I23, M15, D83
Paper type: Empirical study

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1. Introduction

Language proficiency, or what is called multilingualism, has become an essential skill. The internet and access to travel have enabled people from different cultures and countries to connect and interact more frequently than previous generations, making multilingual communication more vital than ever (Mim 2023).
UNESCO, considered the world's leading advocate for education, which is notably the fourth goal of the Sustainable Development Goals for Agenda 2030, has long supported MLE (Multilingual education), beginning with its call for the use of vernacular languages in education in 1953, which has been reinforced since 1999 by the promotion of multilingual education. To date, it considers it a strategy for greater educational inclusion and a catalyst for sustainable development (UNESCO 2025).
In addition, multilingualism is considered beneficial for economic growth, as people with multilingual skills tend to have higher salaries than others. Countries that encourage multilingualism also tend to be successful in exports and have more innovative work environments (Stein-Smith, 2021).
Technology has always played a catalytic role in education, starting with a peripheral role aimed at supporting classroom teaching and gradually becoming centric to the learning process (Bates, 2015). In our context of rapid edtech evolution, learning through digital tools has become an essential condition for higher education in order to maintain the high quality of teaching (Feng et al. 2025).
In the Moroccan context, The French language, although it is characterized as a foreign language in Morocco, has long imposed itself as a vector of socio-professional ascension (Saddiqui 2024). The English language has also begun to gain momentum among new generations, especially with trends of globalization and open markets (R'boul 2022).
According to a Moroccan study dealing with glottophobic challenges in the Moroccan context (Yougsassen 2024) Speakers who do not fully master the linguistic diversity valued in a given society are often victims of linguistic discrimination.
This sociolinguistic dynamic presents a major challenge inviting national institutions to propose educational solutions in order to guarantee equal opportunities for students. On the other hand, Morocco is experiencing a mass demand for training, digital learning is considered as a solution for quality learning (Boumahdi 2021).
In this context, and to follow the progress of modernization and pedagogical innovation and to boost the quality and efficiency of the Moroccan educational ecosystem. The Ministry of Higher Education and Scientific Research has launched an ambitious project called Pacte Esri (The National Strategy for Accelerating the Transformation of Higher Education, Scientific Research, and Innovation System) from 15 February 2022, in which the ministry signed a contract with the language platform Rosetta stone with the objective of foreign language learning for all Moroccan students in higher education.
Although the ministry emphasizes the importance of integrating digital learning tools in line with international recommendations and is investing significantly to provide its students with learning opportunities, the intention to use this tool by students requires further exploration in our context, which opens the door to exploring the question of institutional provision versus student adoption.
Our study aims mainly to examine the feedback of students in relation to this language learning approach based on a model of the acceptance of technology. We opted for the latest version of the Tam model named the UTAUT2 model (Unified Theory of Acceptance and Use of Technology 2).

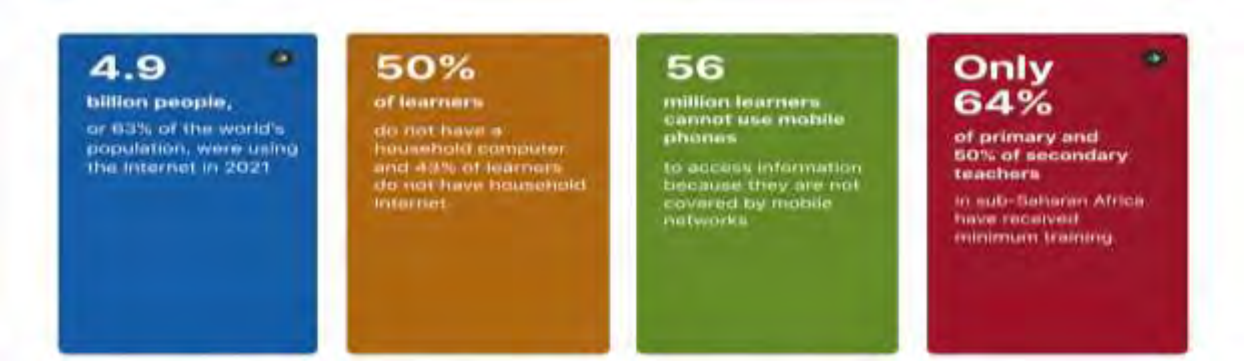
Although the UTAUT2 model has been extensively explored in the literature, many studies have focused on its use in a conventional context, examining individual adoption rather than analyzing the impact of institutional conditions on the use of this educational technology (Acosta-Enriquez et al., 2024; Faqih & Jaradat, 2021; Zacharis & Nikolopoulou, 2022); this is confirmed by a recent meta-analysis noting that previous studies have focused on general usage rather than institutional contextualization (Zheng et al., 2025).
Even in developing countries such as Vietnam, Iraq, or Zimbabwe (Dinh et al., 2025; Hameed & Sumari, 2024; Maune, 2023), studies have also explored voluntary deployment; thus, limited attention has been devoted to the context of this study, where access to this technology is mandated from the top down and adoption remains questionable, which is the gap that this study seeks to address (Dečman, 2015; Lehmann et al., 2023).
Taken together, the central question this article sets out to address is as follows: What factors drive the actual use of the Rosetta Stone platform by Moroccan students, thereby helping to bridge the gap between institutional provision and student effective adoption?
To address this question, this study first establishes the theoretical framework through a literature review, followed by a quantitative empirical methodology to identify the factors driving platform adoption. The article concludes by discussing the findings to provide strategic recommendations for policymakers.

2. Literature review:

2.1 Technology in education

In recent years, digitalization has transformed the global structure of the educational world and changed the practices of all stakeholders including teachers, researchers and professionals (Qureshi et al. 2021). The education sector has taken full advantage of information technology to build the technological backbone that enables new forms of access, interaction, and learning (Mouatassim Lahmini & Tibary, 2025).

Figure 1: Key facts about digital learning.



Source: Unesco report 2023

The major impact of the COVID-19 pandemic was probably a catalyst for changing educational practices (Kotler, Juidette et al. 2024). According to the UNESCO in 2023 report, it estimated that 147 million children missed more than half of their preschool schooling in the last three years, which required urgent intervention to adapt to global circumstances with the help of digitalization.

2.2 Key concepts:

- ***The modern learner profile:***

According to the book essentials of modern marketing (Kotler et al., 2024) the profile of the learner has changed a lot, particularly the Z and the alpha generation - which will soon begin

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their higher studies - are characterized by an information treatment that is well but not in depth, they preempt more information of visual character, tend to quickly forget the news because of a short attention span impacted by the abundance of information and consumption of short content like the so-called "reels" on social media, they value more immersive and interactive experiences, it is a generation more likely to engage in video games and mobilizes several types of devices. All of these characteristics require pedagogical adaptation so that the learning experience is more effective and meets its needs.
Since the new pedagogical form proposed by the Ministry of Higher Education is the adoption of a hybrid learning combining face-to-face language courses and online courses for the validation of the language module, we will focus on the concept of blended learning, which we can define as the integration of online and traditional classroom activities into a planned schedule, pedagogical and added value with part of the time face-to-face replaced by online activity (Dziuban et al. 2018), this combination demonstrated its effectiveness by combining the benefits of both methods (Buhl-Wiggers et al 2022).

- ***Self-paced learning***

Learning at its own pace (self-paced learning) is becoming increasingly important with digital. Students using their connected devices now have the opportunity to study educational content independently and according to their aspirations.
A major challenge comes with this new practice is that learning and its effectiveness will depend on the effort made by the learner and through his hedonic motivation (Englmeier, K. 2024).
The Rosetta platform is part of this method as students are invited to complete the time volumes at their own pace. As a result, several factors can impact the results of this experiment that we will discuss in the following sections.

- ***Computer-Assisted Language Learning***

Computer-assisted language learning (CALL) is often defined as an approach to teaching and language learning in which the computer is used as a presentation aid, the reinforcement and evaluation of the material learned, generally it includes an interactive element using a technological tool (Davies 2002).

- ***Rosetta stone as language learning tool***

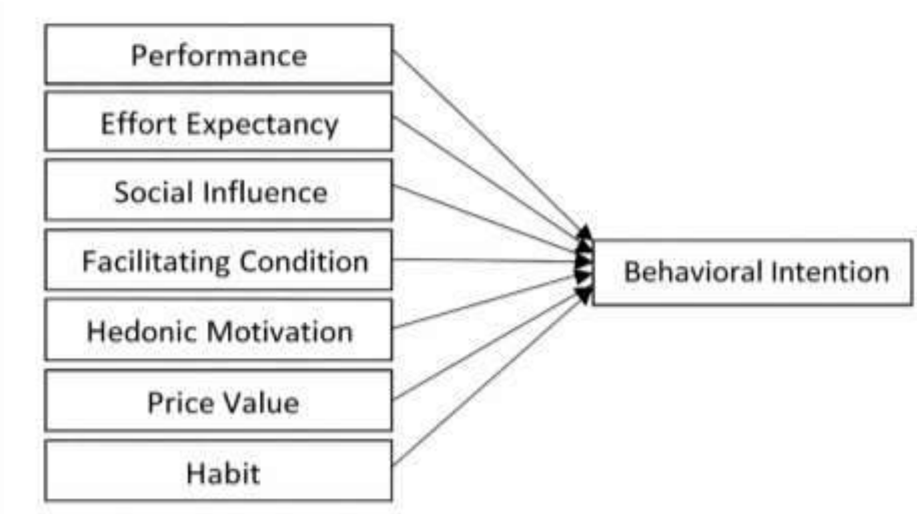
Several scientific studies have accompanied and evaluated the use of Rosetta Stone for language learning. A study conducted in the United States found that using the platform for 55 hours of Spanish improved the level from 56% to 72% of students who took the courses (Vesselinov 2009).
A literature review conducted in Indonesia for oral learning has shown that the platform has effectively contributed to improving listening skills among students (Kurniawan 2021).
A study in Iran also suggests that the use of Rosetta Stone allows for better vocabulary acquisition for learning English (Nst et al. 2023).
These studies illustrate the potential of this platform to improve students' language learning in our Moroccan context.

- ***Theories of technology acceptance***

In order to evaluate the learning experience of the Rosetta Stone platform in higher education, we will present some scientific models. These frameworks address various aspects such as student satisfaction, system effectiveness and student acceptance.
The first version of the technology acceptance model was developed by Davis (1989) with the aim of understanding how information systems are accepted at an individual level. This model was itself inspired by the reasoned action theory (TRA) derived from the field of psychology

and developed by Fishbein and Azjen in 1975 (Juidette, Zraiouil, 2025).
This model is based on key variables, namely perceived utility, perceived ease of use, and behavioral intent to use. The model was developed to offer a more rigorous understanding through the introduction of new variables such as social influence and cognitive factors in the second version in 2000, by authors Venkatesh and Davis Rondan-Cataluña et al. (2015). In 2008, another version was released, adding computer self-efficacy, perception of external control, computer-related anxiety, and enjoyment as new factors developed by Venkatesh and Bala (Juidette, Zraiouil 2025).
The Unified Theory of Acceptance and Use of Technology (UTAUT) is considered a more mature version of the previous model and was proposed in 2003. Its latest version, UTAUT2, was published in 2012 by Venkatesh, Thong, and Xu. This model was characterized by the addition of variables related to gender, age, hedonic motivation, price value, and habit. In our study, we will focus on the evaluation of the Rosetta Stone platform by mobilizing the latest version of the TAM model, which is the UTAUT2 model (Rondan-Cataluña et al. 2015).

Figure 2: Unified Theory of Acceptance and Use of Technology.



Source: Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology.

2.3 Hypotheses Development

Based on UTAUT2 (Venkatesh, Thong, and Xu., 2012), we chose to adopt these factors: Performance, Effort Expectancy, social influence, Social, Facilitating condition, Hedonic Motivation, Price Value and Habit, this study adapts the UTAUT2 variables to the specificities of the Moroccan context following the Pacte Esri recommandations and integrates an exogenous variable the formal exam process to capture the mandatory nature of the learning digital transition. The application of the UTAUT2 model in the Moroccan context remains to be adapted to its specific characteristics; first, this model was designed and validated in different settings, whereas Morocco is among the countries characterized by high power distance and collectivism (Hofstede, 2001), which may affect model variables such as social influence and facilitating conditions. Second, we are applying a model that was originally designed for a generic user experience to a learning context, particularly one where use is mandatory and assessed by a test. This requires an investigation that addresses these specific structural and cultural differences as compared to the basic model.
Venkatesh et al. (2012) identified Performance Expectancy as a key factor in technology usage behavior. Studies have confirmed this finding, with Abbad (2021) confirming that this variable plays a significant role in usage behavior in the context of Moodle use. A study focusing on the

use of mobile applications in an e-learning context also points to the important role of this variable (Imran et al., 2023). However, the relationship between these two variables may not apply in different contexts, such as those in which usage is mandated by the institution, which require further exploration (Brown et al., 2002; Raman et al., 2021).

H1: *Performance expectations positively influence the behavior intention to use the platform.*

Effort Expectancy, which we can describe as the degree of ease in using the platform (Patil, 2023), is also considered a significant factor in behavioral usage. This has been confirmed by several empirical studies in different fields, including LMS, mobile apps, etc. (Tarhini, Hone & Liu, 2015; Mensah et al.,2022; Tomić et al., 2023). But other studies suggest that this effect may diminish as users become more familiar with the system (Dwivedi et al., 2019).

H2: *Effort expectations positively influence the behavior intention to use the platform.*

Social influence is a key factor in the technology acceptance model and a validated contributor to behavioral use (Feng et al., 2025). This has been demonstrated in several emerging contexts such as Jordan (Altawalbeh et al.,2023) and Vietnam (Bui et al. 2020), and particularly in Morocco (Tariq and Aoujil 2023). Morocco is a country characterized by a collectivist culture where individual behavior is commonly influenced by social norms and institutional authority (Hofstede, 2001; Tarhini et al., 2015). In this context, social influence may be shaped by peer opinions as well as teachers' recommendations (Tarhini et al., 2015) as compared to other individualistic cultures. Our study aims to explore this assumption.

H3: *Social influence has a positive impact on the behavior intention to use the platform.*

The conditions facilitating the use of the platform have also been supported by several empirical studies demonstrating its impact on usage behavior (Afolabi, Dlamini, & Evans, 2025; Chou, Wu, & Chao, 2025; Cui et al., 2025). In the Moroccan context, where the country is generally considered a developing region, we observe disparities in internet access and technological infrastructure, which may limit the ability to take advantage of digital learning tools (Venkatesh et al., 2012; Salloum et al., 2019). Consequently, this may influence the extent to which such an approach is accepted. Our study aims to explore this subject (Tarhini et al., 2015).

H4: *Facilitating conditions positively influence behavior intention to use the platform.*

Motivation, which is operationalized as hedonic motivation in the UTAUT2 model, is considered a key antecedent for behavioral intention usage (Venkatesh et al., 2012). This is validated by several empirical studies, citing as an example the meta-analysis by Tamilmani et al., 2019, which assumes a 58% use of hedonic motivation by studies that use the UTAUT2 model. Other studies also confirm this finding (Zhang 2023, Granić, 2022, Tao 2024). On the other hand, a meta-analysis suggests that when the use of a platform is motivated by a utilitarian and extrinsic reason-in our case, the requirement to complete the course in order to validate the language course-the effect of hedonic motivation may become negligible (Tamilmani et al., 2019). Our study aims to further analyze these conditions and verify whether hedonic motivation still plays a positive role in our setting.

H5: *Motivation to continue using the Rosetta platform positively influences behavioral intention of use.*

Regarding the price value factor, several studies have empirically confirmed the perception of cost-benefit on usage intention using the UTAUT2 model. Citing as an example the study by Mehta et al. (2019) in the context of e-learning adoption and Vidal-Silva et al. (2024) for the acceptance of telemedicine in Chile. In this context, the concept of "price value" raises some theoretical ambiguity, as the platform is available for free, which limits the applicability of its original definition based on monetary factors (Venkatesh et al., 2012). Therefore, its role as a predictor of behavioral intentions still requires empirical study in our settings. We therefore postulate the following hypothesis:

H6: *The price value has a positive impact on behavioral intention of use of the platform.*

For the variable Habit in the UTAUT2 model, it has also been proven in several contexts that it is a determining factor in relation to behavioral intention of usage and that the habits developed by students in relation to technology positively reinforce their intention to continue using the platform (Almaiah et al., 2022, Zhang & Yu, 2023).
In mandatory learning settings, students' habit of using the platform may be driven by institutional requirements rather than by a genuine habit that fosters effective learning. Consequently, the effect of habit on the intention to use the platform requires empirical examination.
H7: *Habits positively influence the behavioral intention of use of the platform.*
We introduced an external variable into the UTAUT2 model, namely the exam process, as this proved to be important since students who took the Rosetta Stone training course were required to take a final exam to assess their level. The introduction of the "Exam process" variable is theoretically based on the washback effect, which highlights the role of assessments in influencing students' learning behavior (Alderson & Wall, 1993). Studies on the acceptance of technology-based exams and online proctored examinations have shown that assessment impacts behavioral intention to use in an educational context (Fink et al., 2023; Raman et al., 2021). In mandatory educational settings, the use of platforms may be driven by assessment requirements rather than genuine engagement with the learning platform, raising questions about whether the observed usage reflects genuine behavioral intent or merely compliance.
H8: *The exam process positively influences the behavioral intention of using the platform.*

3. Methodology

3.1 Research Design

The main aim of this study is to evaluate the experience of students involved in required training on the Rosetta Stone platform and explore their intention to use it based on the UTAUT2 model, and more specifically to investigate the transition from the institutional provision to the adoption of the platform. First-year university students and doctoral students were all required to take language courses. Students are supposed to take a test to determine their preliminary level and proceed with the courses according to a defined number of hours. Each student will take the test at the end of the training to assess their level after use. The platform offers access to several languages according to user preferences, but only French and English were included in the evaluation.
Our study is based on a quantitative cross-sectional approach in which data was collected over a single period in order to explore our research question through the lens of our hypotheses. These hypotheses are based on the revised UTAUT2 model, which uses the following variables: performance, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit by adding an additional variable which is the course of the exam process, and behavioral intention as the dependent variable. Since our variables are quantitative, we opted for a Likert scale (1932) based on Churchill's paradigm (1979).

3.2 Sample and data

Our study focuses on the evaluation of the online learning experience, Moroccan students taking Rosetta stone courses for the academic year 2024-2025, a population estimated at 700,000 According to the ESRI Pact 2030 launched by the Ministry of Higher Education, of Scientific Research and Innovation (2023). Since there was no access to a database of students across Morocco, the use of a probabilistic method was not possible, which led us to adopt a convenience sampling method (Malhotra, 2014) through a very broad distribution using a national network of language professors at all Moroccan universities. This method allowed us to collect a massive sample of 1,548 responses. However, we must note that the generalization

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of the results should be treated with caution, as the sample may not reflect the diversity of the student population.
67.9% of the respondents are under 21 years old and two-thirds of our sample are women. Two-thirds study at university while one-third are business schools with a minority of engineering schools.

3.3 Data analysis technique and research model

To process our data, we opted for SPSS software. Our data analysis was as follows: first, we cleaned and coded our data, as the Likert scale was in the form of statements, so we converted it into numbers from 1 to 5; then, a descriptive analysis was conducted, followed by an ACP analysis and, finally, the application of our regression.
As mentioned above, we deployed the variables of the UTAUT2 model by adding another variable, which is exam process:

- Behavioral intention (BI)
- Performance expectations (BE)
- Effort expectancy (EE)
- Social influence (SI)
- Facilitating conditions (FC)
- Hedonic motivation (HM)
- Price value (PV)
- Habit (H)
- Exam process (EP)

Figure 3: My conceptual model based on UTAUT2 (Venkatesh, Thong and Xu, 2012)

Source: Prepared by the authors

Our survey is based on our chosen model divided into nine parts, the first eight parts consisting of two elements each are inspired by our eight variables, the last part concerns the exam process which consists of 3 questions.
The items used in the survey are primarily based on the UTAUT2 scale (Venkatesh et al., 2012) and have been adapted to suit our specific context; a pilot study was conducted with language professors to ensure that the terminology is appropriate for graduate students. Some items were phrased in reverse order to limit confusion during data collection.
The questions are broken down as follows:

Table 1: Questions by construct

Construct	Item
Performance Expectations	Using the Rosetta platform has helped me improve my language level.
	Rosetta Stone does not help me achieve optimal performance in my language studies.
Effort Expectations	The user experience on the Rosetta platform is fluid, which allows me to follow my courses efficiently.
	The placement test allowed me to precisely assess my language level and improve it.
Social Influence	The perceptions of my entourage (classmates, friends...) influence my level of engagement with the Rosetta platform.
	The recent buzz on social networks around the Rosetta platform influences my perception and use of it.
Facilitating Conditions	I have the necessary technological tools to effectively follow the courses of the Rosetta platform.
	I received all the support necessary to facilitate the start of use of the Rosetta platform.
Hedonic Motivation	I am motivated to continue using the Rosetta platform for my learning.
	If the Rosetta platform was not a mandatory module, my motivation to use it would decrease.
Price Value	If the Rosetta platform became a paid one, my intention to continue using it would remain high.
	I would perceive the Rosetta platform in the same way if it became paid.
Habit	The Rosetta platform is now an integral part of my language learning habits.
	I easily allocate the time required by my school to use the Rosetta platform.
Behavioral Intention	I use the Rosetta platform regularly for my language learning.
	I spend a significant amount of my time using the platform's main features (interactive exercises, videos, etc.).
Exam Process	The language exam was conducted in good conditions.
	Thanks to the courses on the Rosetta platform, I felt well prepared for the exam.
	The content of the tests seemed to me in line with the content studied during the course.

Source: Prepared by the authors

Our model will follow a linear regression considering behavioral intention as our dependent variable and the other variables, namely performance, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and the exam process, as independent variables. Our regression equation is as follows:

$$BI=\beta 0 + \beta 1\ BE + \beta 2\ EE + \beta 3\ SI + \beta 4\ FC + \beta 5\ HM + \beta 6\ PV + \beta 7\ H + \beta 8\ EP + \varepsilon$$

With ε = residuals

4. Results analysis

4.1 Descriptive analysis

Before proceeding with the descriptive analysis, we recoded the Likert scale responses by assigning a score of 1 to 5 (1 = strongly disagree and 5 = strongly agree) to all 1,548 responses. The results of the preliminary analysis gave us an idea of the students' perceptions of the different constructs. The results indicate an average ranging from 1.838 to 3.286 and a standard deviation that indicates moderate dispersion (1.283 and 1.561).
The table below presents the results of our descriptive analysis, calculating the mean and standard deviation for each item. To facilitate data manipulation, we have opted to use abbreviations for the constructs and items.

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Table 2: Item descriptive statistics

Construct	Item	N	Mean	SD
BE	BE1	1548	2.706	1.451
	BE2	1548	2.818	1.485
EE	EE1	1548	2.38	1.435
	EE2	1548	2.957	1.477
SI	SI1	1548	2.39	1.337
	SI2	1548	2.402	1.367
FC	FC1	1548	3.02	1.487
	FC2	1548	2.866	1.433
HM	HM1	1548	2.579	1.552
	HM2	1548	3.286	1.561
PV	PV1	1548	1.838	1.283
	PV2	1548	1.978	1.343
H	H1	1548	2.487	1.358
	H2	1548	2.419	1.363
BI	BI1	1548	2.612	1.39
	BI2	1548	3.04	1.424
EP	EP1	1548	3.208	1.453
	EP2	1548	2.463	1.41
	EP3	1548	2.581	1.368

Source: Prepared by the authors

Before we begin our Principal Component (MCA) analysis, it is imperative to verify the validity and reliability of the data.
For our factor analysis, it is necessary to have a sample greater than 4 times our number of items, in the order of 19, which is largely surplus given that our sample consists of 1548 respondents. We choose the score calculation, the Kaiser-Meyer-Olkin (KMO) index and the Bartlett sphericity test.
With data manipulation in the SPSS software, the results give us a value of 0.941; this is considered excellent KMO > 0.6, which shows that our variables are correlated and allow us to perform an ACP.
The Bartlett test, in turn, indicates a score of less than 0.05 confirming that correlations between variables are not random.

4.2 Principal Component Analysis (PCA)

Now we proceed to the second stage, which is the Principal Component Analysis, an important phase in order to define the most relevant constructs for our study.
According to the table of the total variance adopted by the SPSS software and the Kaiser criterion, the first 4 components have a proper value greater than 1 and explain a percentage of 58.1%, which is sufficient to summarize our data
Component 1: 7.651 representing 40.268% of the total variance.
Component 2: 1.576 justifying 8.293% variance.
Component 3: 1.238 justifying 6.518% variance.
Component 4: 1.075, representing 5.656% of variance.
Since this study takes a confirmatory rather than an exploratory approach by applying the UTAUT2 model, all constructs were retained to preserve the theoretical integrity of the model.

The grouping of these concepts into four components is explained by the emergence, in our context where digital training is mandatory, of certain closely related and interdependent concepts, namely intrinsic motivation, social influence, and effort anticipation.
Although relying on theoretical foundations rather than purely data-driven criteria constitutes a methodological limitation, this decision was necessary to maintain structural consistency with our original model, which allows us to explore the specificities of our context. Overall, the retained components explain 79.335% of the total variance, indicating a satisfactory level of explained variance.
We now move on to the quality matrix of the overall model presentation. We note that all the elements have an extraction value greater than or close to 0.5 except for the elements "I have the technological tools necessary to effectively follow the courses of the Rosetta platform" with a score of 0.478 and "I spend a significant amount of my time using the platform's core features " With a score of 0.444, they have a relatively low similarity, which suggests that they are less well explained by the core components.

Table 3: Summary Table of Validity and Reliability Analysis Results

Variable	Nb.items	KMO	%variance	Cronbach's Alpha
Performance expectations	2	500	58,574	293
Effort expectations	2	500	77,447	709
Enabling conditions	2	500	72,032	612
Social influence	2	500	73,586	641
Hedonic motivation	2	500	63,484	424
Habits	2	500	76,360	690
Price value	2	500	79,985	750
Behavior intention	2	500	77,911	716
Exam process	3	662	68,380	765

Source: Prepared by the authors

We find that all our KMO indices are greater than 0.5 and the percentage variance explained by each factor is greater than 60% for most variations.
The Cronbach index is close to 0.6, which we can consider acceptable and our variables are reliable, except for two variables, that of performance expectations and hedonic motivation.
We assumed that the alpha of Cronbach is low because of the number of elements which is not sufficient. After checking with the calculation of the Pearson coefficient which applies to two items, we found that r was always less than 0.3, so the items of these two variables are not correlated. Both variables are characterized by the fact that the second items were cancelled.
Example:

- ***Performance expectations:***

Item 1: Using the Rosetta platform has helped me improve my language skills.
Item 2: Rosetta Stone does not help me achieve optimal performance in my language studies.
The inclusion of the reverse-scored item (Item 2) raised a reliability issue, which led to its exclusion. Although retaining only a single item for a concept may constitute a methodological limitation, this adaptation is justified by the direct and concrete nature of the concept, which the literature review permits in this context (Bergkvist & Rossiter, 2007).
We therefore decide to leave only the first element to present the variables Expectation of performance and hedonic motivation since these are important for our study and we cannot eliminate them.
After verifying the reliability and validity of our scales, we will proceed to verify the assumptions.
But first we will create new variables by calculating the arithmetic average of variables with several items.

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4.3 Verifying Hypotheses

This stage of our study will allow us to validate or reject our preliminary assumptions, we choose linear regression as the basis for calculation, we consider the actual usage behavior as our dependent variable and check the regression between the eight independent variables that remain. Before we start the regression, we need to check certain premises.

- ***Residual Independence***

Table 4: Residual Independence using Durbin Watson test

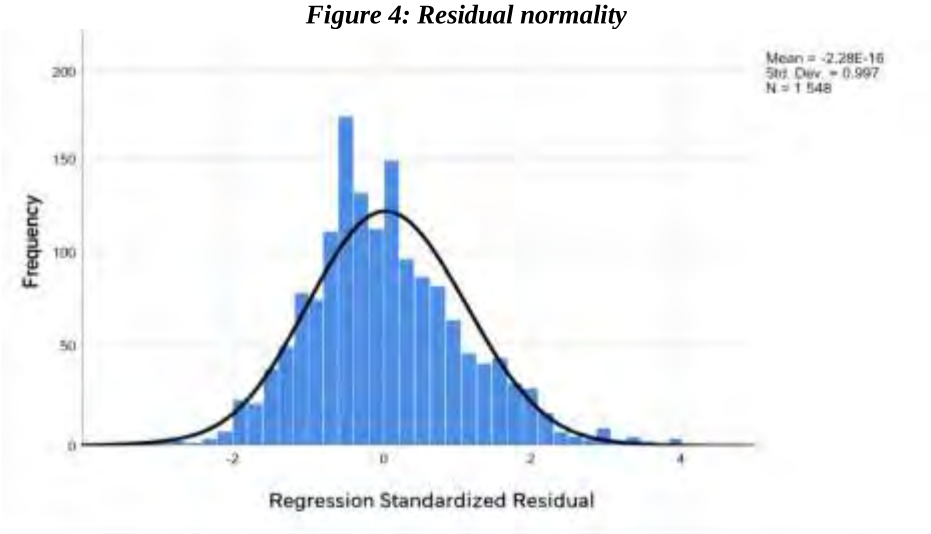
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,731[a]	535	532	84,936	535	221,011	8	1539	0	2,004

Source: Prepared by the authors

We note that the value of the Durbin-Watson test is close to 2, so residue independence is verified.

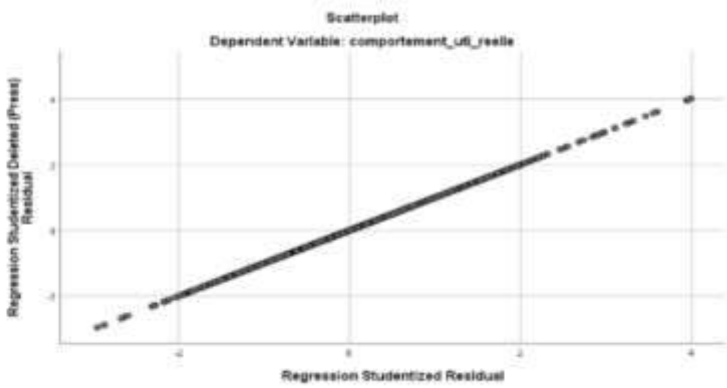
- ***Residual Normality***

Figure 4: Residual normality



Source: Prepared by the authors

Figure 5: Histogram of the standardized residues

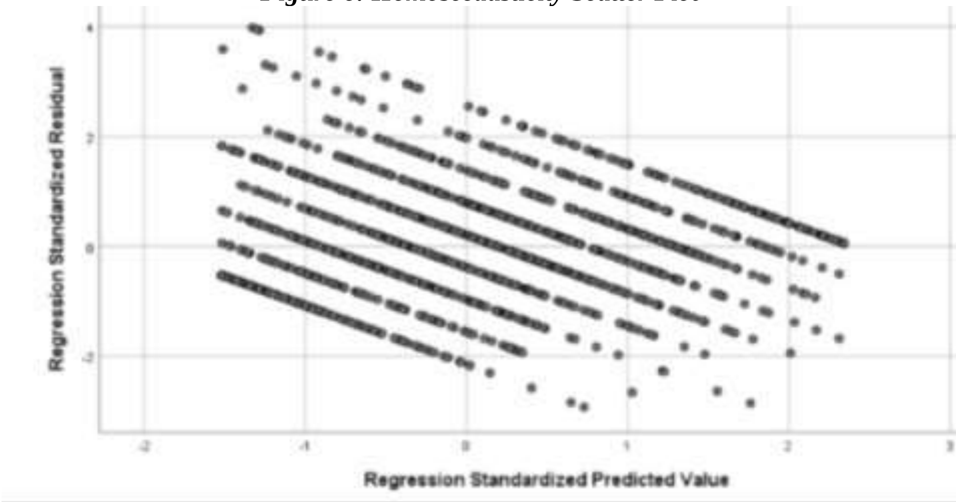


Source: Prepared by the authors

We observe that the residues follow a normal law, the normalized residue histogram follows the Gauss curve and we also find that all data are closer to the reference line in the P-P diagram. So, we can say that the normality of our data is verified.

- ***Homoscedasticity***

Figure 6: Homoscedasticity Scatter Plot



Source: Prepared by the authors

The histogram of the point clouds indicates a problem of heteroscedasticity, which manifests itself in the formation of residues forming very visible lines. To correct this effect, we opted for the robust standard error method HC3. The latter allowed us to adjust the standard errors by integrating the weighted residuals into the covariance matrix.
The results of this calculation are summarized in the following table, to which we have integrated only variables with a significant p-value and a standardized error.
To move to linear regression, we must ensure other premises including the absence of collinearity.

- ***Multicollinearity***

Table 5: Coefficients table

Variable	Coefficient (β)	HC3 Standard Error	p-value
Constant	0.5709	0.0635	< 0.001
Performance Expectancy	0.0654	0.0258	0.011
Effort Expectancy	0.0049	0.0304	0.872
Social Influence	0.0405	0.0226	0.072
Facilitating Conditions	0.1002	0.0241	< 0.001
Hedonic Motivation	0.0655	0.0258	0.011
Price Value	0.0258	0.0218	0.237
Habits	0.4157	0.0337	< 0.001
Exam Process	0.1583	0.0311	< 0.001

Source: Prepared by the authors

All VIF values are below the critical threshold of 5 and tolerances are above 0.1. Our model is therefore considered robust in terms of multicollinearity.

Table 6: Linear Regression Model Summary and ANOVA

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,731[a]	535	532	84,936	2,004	1	,731[a]	535	532	84,936

Model	Source	Sum of Squares	df	Mean Square	F
1	Regression	1,275,511	8	159,439	221,011
	Residual	1,110,244	1539	721	
	Total	2,385,755	1547		

Source: Prepared by the authors

The overall model is significant and explains well the variance of our dependent variable, namely the actual use of the platform with an R-square of 53.5%.
The Durbin Watson test also shows a value of 2, indicating that there is no autocorrelation of the residue.

4.4 The multiple regression equation

The multiple regression equation, which is obtained after analyzing the coefficients of each predictor in the table above, is:

$$BI = 0.5709 + 0.0654\ PE + 0.0049\ EE + 0.0405\ SI + 0.1002\ FC + 0.0655\ HM + 0.0258\ PV + 0.4157\ H + 0.1583\ EP + \varepsilon$$

With ε = residuals

The results of the linear regression show that some variables clearly have an impact on behavioral intention, with Performance expectations (H1) having a positive and significant impact ($\beta = 0.065$, $p = 0.0112$), as do Enabling conditions (H4) ($\beta = 0.100$, $p < 0.001$), Hedonic motivation (H5) also ($\beta = 0.065$, $p = 0.0112$), Habits (H7), which is considered the most powerful predictor in the model ($\beta = 0.416$, $p < 0.001$), and finally the Exam process (H8), confirming the positive impact of evaluation on intention to use.
On the other hand, Effort expectations (H2) and Price value (H6) do not contribute significantly, with respective indicators of ($\beta = 0.005$, $p = 0.859$) and ($\beta = 0.026$, $p = 0.226$), leading us to reject their hypothesis, while Social influence (H3) has a marginal impact ($\beta = 0.041$, $p = 0.072$).
The validation of our eight respective hypotheses is summarized in the following table.

Table 7: Summary of Hypotheses Validation

Hypothesis	Validation
H1	Supported
H2	Not supported
H3	Marginally supported
H4	Supported
H5	Supported
H6	Not supported
H7	Supported
H8	Supported

Source: Prepared by the authors

5. Discussion

So, after our regression analysis, we find that certain variables contribute significantly to the behavioral intention to use the Rosetta platform. These variables are, in order of impact: Habit (H) with a very strong impact, followed by Exam Process (EP) and Facilitating Conditions (FC). While other variables such as Performance Expectations (PE), Hedonic Motivation (HM), and Social Influence (SI) have a weaker impact, Perceived Value (PV) and Effort Expectancy (EE) have an almost non-existent contribution to the model.
Habit, considered in our study to be the most important factor, is consistent with previous studies that used the same UTAUT2 model. For example, a study conducted in an e-learning context also found that habit is the strongest predictor in the model (Raman et al., 2021). Another study also came to the same conclusion regarding expectations of ChatGPT artificial intelligence at a Polish state university (Strzelecki, 2023). While the literature defines this variable as an automated determinant of behavior, our context reflects a routine of academic compliance, in which students incorporate the use of the Rosetta Stone platform into their daily routines in order to complete their course module for the semester.

Regarding the exam process factor, the fact that students are aware that they will be taking an exam supports their intention to use the Rosetta Stone platform to validate their module. Its significant role is also confirmed by studies evaluating the importance of the assessment environment on the acceptance of technology similar to our educational context, notably the study by Fink et al. (2023) and Raman et al. (2021). The role of this variable, which appears to be prominent, can be explained through the lens of Constructive Alignment Theory (Biggs, 2003) in what is known as the "backwash effect of assessment." Students place greater value on the pedagogical practices they deem necessary for passing their course; therefore, the "exam process" variable reflects not only a contextual factor but also the essence of the use of the Rosetta Stone platform.

For the Facilitating conditions factor, our study reveals a significant impact of this factor on behavioral intention to use the platform. Therefore, in our context, the infrastructure of the technological solution and the support of the institution positively influence the use of technological solutions. This finding is also supported by studies that reached the same conclusions (Tahir, 2023; Tao, 2024)).

For the Performance expectations and social influence factors, we found that they have a positive but relatively modest impact when compared to previous factors in our model. These results are consistent with other studies that have found a moderate contribution to the UTAUT2 model (Zheng et al., 2025; Widjaja et al., 2020). In this mandatory setting, it seems that vertical institutional authority counteracts the horizontal peer pressure, which explains why our respondents seem to engage in the behavior regardless of social validation.

This study found that hedonic motivation remained positive despite the mandatory nature of the context. The "cognitive evaluation theory" (Deci, 1975) posits that mandatory evaluation systems generally undermine hedonic motivation. Drawing on the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984), we can support this hypothesis by arguing that the platform, through its interactive features, provides a mechanism that promotes learning and motivation.

Moving on to the final factors that do not contribute significantly or whose impact is negligible, our study shows that price value does not influence behavioral intention to use, particularly in our case where resources are provided free of charge by the university. The same applies to effort expectancy, assuming that students are already familiar with this type of platform, which makes the impact of this factor insignificant. Previous studies support these findings for these two variables (Liu et al., 2025; Alruthaya et al., 2025).

Following these findings, it is recommended that educational departments capitalize on the integration of the platform into the formal exam process given its importance as a determining factor in usage. To optimize this experience, institutions should empower facilitating conditions by resolving technical issues and providing comprehensive documentation at the beginning of each module. Supporting habit formation and fostering hedonic motivation, policymakers can ensure students fully benefit from the potential of this modern digital tool, thereby maximizing the impact of the learning pedagogical innovations.

6. Conclusion

The results of the analysis of the main components allowed us to examine the various factors that can influence the behavior intention of the Rosetta platform. This so-called analysis confirmed that assumptions, performance expectations, facilitating conditions, motivation to continue, habits and the course of the exam greatly influence the actual use of the platform. Social influence was marginally validated, while effort expectations and perceived value were not confirmed.

Our study contributes to the current literature by testing the UTAUT2 model in a mandatory institutional setting, where we found that the primary determinant is habit—which we considered to be a routine form of academic compliance—as well as the exam process, which captures the essence of institutional coercion.

Regarding the managerial implications of this study, it is important that exams accurately reflect course content, as this is a strong determinant of acceptance of such platforms. It is also recommended that faculty ensure clear communication of the objectives of these platforms and provide all necessary information, such as multimedia and technical support, to facilitate the adoption of digital learning platforms.

At the national level, it is recommended that universities provide internet access and the necessary infrastructure to ensure equitable use of digital tools, thereby ensuring successful adoption across the national territory.

As for the limitations of our study, we can say that, first, a significant part of the model has not yet been explored, which would allow for a comprehensive understanding of the intention to use in our context using a model that integrates other influencing factors. The use of a non-probabilistic convenience sample may limit the generalizability of the results and prevent a perfect representation of the entire Moroccan student population.

For the variable Performance expectancy, measurements had to be taken using a single-item scale, which may have weakened the results for this variable. Finally, structural validity was limited by a forced nine-component extraction during the principal component analysis (PCA) to preserve the consistency of the theoretical model, which may compromise our results.

A longitudinal approach may be more rigorous in order to detect changes in familiarity with the platform. Adding an additional variable to the model such as Perceived Coercion would allow for a more precise quantification of the psychological pressure exerted by academic guidelines.

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