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Technology Acceptance Model for Smartphone Use in Higher Education

Modelo de Aceptación de la Tecnología para el uso del Smartphone en la Educación Superior

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ABSTRACT

Context. The technology acceptance model (**TAM**) is a theoretical framework that consists of perceived usefulness (**PUS**), perceived ease of use (**PEU**), attitude toward using (**ATT**), behavioral intention to use (**USI**), and actual system use. Here, actual system use is posed by the smartphone use in higher education (**SHE**) described such as student self-management **(MNG),** student learning results **(LRS),** student achievements perceptions **(SFB),** student cost-benefits perceptions **(VCB),** and student expectations **(EXP)** that help to understand and explain how students' acceptance and adoption of smartphone technology could be better achieved. Nowadays, after the **COVID-19** pandemic, student motivation (**MTV**) and student quality perceptions (**SQY**) are two factors that reinforce the **TAM** model.

Problem. The research confronts challenges from the dynamic and rapidly changing technology and education environments. The **post-COVID-19 era** introduces uncertainties, potentially affecting the **TAM-SHE** model's long-term sustainability. The fluidity of student preferences and technological advancements obstruct the establishment of a universally applicable framework for smartphone acceptance in education. This raises concerns about the model's adaptability and generalizability across diverse educational settings, emphasizing the careful consideration of evolving factors. Therefore, the following research question is proposed: What is the **TAM** for **SHE** empirical framework as an innovative tool?

Purpose. The research aims to explore students' acceptance of smartphone technology in education using the technology acceptance model (**TAM**), focusing on perceived usefulness, ease of use, attitude, intention, and actual system use within smartphone use in higher education (**SHE**) in the context of **post-COVID-19** era, the study considers student motivation (**MTV**) and student quality perceptions (**SQY**) as crucial factors enhancing the **TAM-SHE** framework.

Methodology. We determined the following steps: **Step 1.** A qualitative study based on the Delphi Panel-Focus Group and Analytic Hierarchy Process (**AHP**) to determine the questionnaire **TAM-SHE** among **three specialists**: **1** information technology expert, **1** information technology professor, and **1** university student related to **TAM** for **SHE** and questioned about the items and factors related to the preliminary questionnaire design.

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Step 2. A literature review to explain the items and factors for the questionnaire (*ex-ante*) proposal involved in the design will be applied to more than **523** Mexican university students in the **second semester of 2023.**

Step 3. Once all the data in the questionnaires had been collected were probed regarding the **Cronbach Alpha** reliability. A quantitative study on confirmatory factor analysis based on partial least square structural equation modeling (**PLS-SEM**) with **SMART PLS (4.0.9.8)** was used to probe convergent, discriminant, and nomological validity for the final conceptual **TAM-SHE** framework.

Theoretical and practical findings. We propose a robust empirical **TAM-SHE** framework able to explain and predict how their factors enhance smartphone use in higher education.

Transdisciplinary and sustainable innovation originality. The utilization of smartphones in higher education contributes to sustainable development by reducing educational disparities between students from different socioeconomic backgrounds. Additionally, mobile learning aligns with the Sustainable Development Goals (**SDGs**), particularly **SDG4**, by advancing sustainable quality higher education. Furthermore, it facilitates worldwide access to education, promoting a more inclusive and equitable learning environment

Conclusions and limitations. For the **post-COVID pandemic** era, more studies are necessary to verify the new student motivations (**MTV**), student quality perceptions (**SQY**), and the actual system use factors to facilitate mobile technology in use for higher education through the technology acceptance model (**TAM**).

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RESUMEN

Contexto. El modelo de aceptación de tecnología (**TAM**. *Technology Acceptance Model*) es un marco teórico que consta de utilidad percibida (**PUS.** *Perceived Usefulness*), facilidad de uso percibida (**PEU.** *Perceived Ease of Use*), actitud hacia el uso (**ATT.** *Attitude Toward Using*), intención de comportamiento de uso (**USI.** *Behavioral Intention to Use*) y uso real del sistema. Aquí, el uso real del sistema está planteado por el uso del smartphone en la educación superior (**SHE**. *Smartphone use in Higher Education*), descrito como la autogestión del estudiante (**MNG**. *Student Self-Management*), los resultados del aprendizaje del estudiante (**LRS.** *Student Learning Results*), las percepciones de los logros del estudiante (**SFB.** *Student Achievements Perceptions*), las percepciones de costos y beneficios del estudiante (**VCB**. *Student Cost-Benefits Perceptions*) y las expectativas del estudiante (**EXP.** *Student Expectations*), que ayudan a entender y explicar cómo se puede lograr mejor la aceptación y adopción de la tecnología del smartphone por parte de los estudiantes. Hoy en día, después de la pandemia de **COVID-19**, la motivación del estudiante (**MTV.** *Student Motivation*) y las percepciones de calidad del estudiante (**SQY**. *Student Quality Perceptions*) son dos factores que refuerzan el modelo **TAM**.

Propósito. La investigación tiene como objetivo explorar la aceptación de la tecnología del smartphone en la educación de los estudiantes utilizando el modelo de aceptación de tecnología (**TAM.** *Technology Acceptance Model*), centrándose en la utilidad percibida, la facilidad de uso, la actitud, la intención y el uso real del sistema dentro del uso del smartphone en la educación superior (**SHE.** *Smartphone use in Higher Education*) en el contexto de la era **post-COVID-19**. El estudio considera la motivación del estudiante (**MTV.** *Student Motivation*) y las percepciones de calidad del estudiante (**SQY.** *Student Quality Perceptions*) como factores cruciales que mejoran el marco **TAM-SHE**.

Problema. La investigación enfrenta desafíos de entornos tecnológicos y educativos dinámicos y cambiantes. La era **post-COVID-19** introduce incertidumbres que podrían afectar la sostenibilidad a largo plazo del modelo **TAM-SHE**. La fluidez de las preferencias de los estudiantes y los avances tecnológicos obstaculizan el establecimiento de un marco universalmente aplicable para la aceptación de smartphones en la educación. Esto plantea preocupaciones sobre la adaptabilidad y generalizabilidad del modelo en diversos entornos educativos, enfatizando la consideración

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cuidadosa de factores en evolución. Por lo tanto, se propone la siguiente pregunta de investigación: ¿Cuál es el marco empírico **TAM** para **SHE** como una herramienta innovadora?

Metodología. Determinamos los siguientes pasos: **Paso 1**. Un estudio cualitativo basado en el Panel Delphi-Focus Group y el Proceso Analítico de Jerarquía (**AHP**) para determinar el cuestionario **TAM-SHE** entre tres especialistas: 1 experto en tecnología de la información, 1 profesor de tecnología de la información y 1 estudiante universitario relacionado con **TAM** para **SHE**, cuestionados sobre los elementos y factores relacionados con el diseño preliminar del cuestionario. **Paso 2.** Una revisión de la literatura para explicar los elementos y factores del cuestionario (ex-ante) propuestos que se aplicarán a más de **523** estudiantes universitarios mexicanos en el segundo semestre de 2023. **Paso 3**. Una vez que se recopilaron todos los datos en los cuestionarios, se examinaron en cuanto a la confiabilidad del **Alfa de Cronbach.** Se utilizó un estudio cuantitativo de análisis factorial confirmatorio basado en el modelado de ecuaciones estructurales de mínimos cuadrados parciales (**PLS-SEM**) con **SMART PLS (4.0.9.8)** para probar la validez convergente, discriminante y nomológica del marco final **TAM-SHE**.

Hallazgos teóricos y prácticos. Proponemos un modelo conceptual **TAM-SHE** empírico sólido capaz de explicar y predecir cómo sus factores mejoran el uso del smartphone en la educación superior.

Originalidad desde el punto de vista transdisciplinar y de innovación sostenible. El uso de teléfonos inteligentes en la educación superior contribuye al desarrollo sostenible al reducir las disparidades educativas entre estudiantes de diferentes orígenes socioeconómicos. Además, el aprendizaje móvil se alinea con los Objetivos de Desarrollo Sostenible (**SDG**), particularmente el **SDG4,** al avanzar en una educación superior sostenible y de calidad. Además, facilita el acceso mundial a la educación, promoviendo un entorno de aprendizaje más inclusivo y equitativo.

Conclusiones y limitaciones. Para la era postpandémica de **COVID**, se necesitan más estudios para verificar las nuevas motivaciones de los estudiantes (**MTV**), las percepciones de calidad del estudiante (**SQY**) y los factores de uso real del sistema para facilitar la tecnología móvil en la educación superior a través del modelo de aceptación de tecnología (**TAM**).

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1. INTRODUCTION

The Technology Acceptance Model (**TAM**) has been widely used to study users' intentions to adopt and use various technologies in different contexts, including smartphone technology in education Fuchs (2022). During the **COVID-19** pandemic, the global education system faced significant challenges, leading to a rapid shift to online teaching. In this context, the successful implementation of mobile learning in higher education has become crucial, emphasizing the importance of understanding the acceptance of these technologies among university teachers and students (Tang et al., 2021). Several studies have focused on the acceptance of mobile technology in education during the **post-COVID-19 era**, highlighting the need to integrate existing theories and models to develop a comprehensive understanding of the factors influencing the adoption of these technologies (Estriegana et al., 2023; Fuchs, 2022; Tang et al., 2021). For instance, the extension of **TAM** to include psychological variables such as self-efficacy and self-determination theory has been proposed to provide a more comprehensive model for understanding technology acceptance among university students (Rosli & Saleh, 2023).

In summary, the **post-COVID-19** era has underscored the significance of the **TAM** in studying the adoption of smartphone technology in university education. By integrating additional factors and theories, **TAM** continues to evolve to provide a robust framework for understanding the complex dynamics of technology acceptance in the education sector, such as this research, the smartphone uses in higher education (**SHE**).

2. CONTEXT DESCRIPTION

Latin America faces significant education challenges, with high drop-out rates, adult illiteracy, and limited access to quality education, particularly affecting low-income urban, rural, and indigenous communities (UNESCO, 2012)**.**

The **COVID-19** pandemic caused several difficulties and disruptions in higher education In Mexico, for instance, students faced challenges such as setting up a study area in their house equipped with books, computers, and fast internet access. Among Mexican students, 39.1% lacked internet service, and up to 30% of students had to access their assignments via cellphone (Chans et al., 2023), 44.3% of households owned computers, while 56.4% had internet connectivity (Zapata-Garibay et al., 2021).

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George-Reyes et al. (2023), examined the study habits of university students over a span of 700 days during the pandemic. The results revealed that students acquired digital literacy, enhanced learning experiences, increased motivation to learn, and heightened engagement.

Additionally, educators were compelled to acquire technological skills for educational delivery, and the Mexican National Education System endeavored to align with government directives in adapting to the challenges posed by the pandemic, as outlined by Vega et al. (2022).

Mexican students declared that the expenses that increased in their homes in the highest proportion were electricity, mobile phone data, and internet service (Zapata-Garibay, et al. 2021)**.** Hence, mobile learning through smartphones has been identified as an important alternative during the pandemic (Naciri et al., 2020). In 2022, the number of mobile phone users in Mexico amounted to nearly 94 million, up from approximately 42 million users back in 2009; 79.2 % of households in Mexico owned a mobile phone (Statista, 2023). Mexico has adopted strategies to make digital textbooks and learning and assessment resources accessible to all students (OECD, 2023).

3. LITERATURE REVIEW

The mobile learning definition involving the use of smartphone, according to UNESCO (2012), is:

Mobile learning involves the use of mobile technology, alone or in combination with any other type of information and communication technology (ICT), in order to facilitate learning at any time and place. It can be done in many different ways: there are those¿ who use mobile devices to access pedagogical resources, connect with other people or create content, both inside and outside the classroom. Mobile learning also encompasses efforts to achieve broad educational goals, such as effective management of school systems and improved communication between schools and families.

The shift to remote learning has brought about various obstacles for students and teachers alike. One notable challenge is encountered by Mexican students who struggle to establish suitable study environments at home, complete with essential resources such as books, computers,

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and high-speed internet. Moreover, as many as 30% of students are compelled to rely on their cell phones to access assignments.

Additionally, students from families with lower educational backgrounds face limited opportunities to engage with digital technology besides other challenges such as time management, internet connectivity, and difficulties in following instructions have been reported (Zapata-Garibay et al., 2021). Smartphone usage among students has increased, with a focus on accessing online news and educational content (Tejedor et al., 2020).

These findings are the basis of this paper to suggest a framework as a contribution to the technology acceptance model (**TAM**) to develop new strategies to enhance smartphone use in higher education (**SHE**) in Mexico.

3.1. The smartphone as an innovative tool in higher education in the post-COVID-era and its contribution to sustainable development

The use of smartphones in higher education has been a key focus in the **post-COVID era**, with studies highlighting their potential for enhancing student engagement and learning (Okpanum 2022, Koff 2020). However, the digital divide remains a concern, with some students having limited access to devices (Mella-Norambuena et al., 2021). The use of digital resources, including videoconferencing tools and educational videos, has become widespread, but there is a need for reflection on their pedagogical application (Rodríguez & Pulido-Montes, 2022). The transition to online learning has had a significant impact on academia and students, with potential long-term consequences (Abu-Talib 2021).

The utilization of smartphones in higher education contributes to sustainable development by reducing educational disparities between students from different socioeconomic backgrounds (Alam & Forhard, 2023). It enhances 21st-century skills development, bridging the gap between basic and higher-order thinking skills (Lang & Sorgo, 2024). Additionally, mobile learning aligns with the Sustainable Development Goals (SDGs), particularly SDG4, by advancing sustainable quality higher education (Maketo et al., 2023) . Furthermore, it facilitates worldwide access to education, promoting a more inclusive and equitable learning environment (Asadulla, et al.2023).

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3.2. How is related the smartphone use in higher education with the technology acceptance model

The relationship between smartphone use in higher education and the Technology Acceptance Model (**TAM**) in the **post-COVID era** has been a subject of study. Several research papers have explored this relationship, indicating that **TAM** can be used to determine students' behavioral intentions toward smartphone technology in the classroom. **TAM** has been widely employed to predict and explain users' intentions to adopt smartphone technology (Fuchs, 2022; Matzavela & Alepis, 2021).

Additionally, previous studies have used **TAM** to examine the acceptance and adoption of smartphones for learning, particularly in the context of mobile learning in higher education (Iqbal & Bhatti, 2015). These studies reflect the growing interest in understanding the acceptance and adoption of smartphone technology in higher education, especially in the **post-COVID era** (Shanmugapriya et al., 2023).

In December 2023, using in *all fields= "Technology Acceptance Model"* and *"Smartphone Higher Education"* in publication years: *"2020-2023"* in the **Web of Science** database, were found: **29 documents** broken down into 4 (2023), 4 (2022), 12 (2021), 9(2020). However, only **10 documents** were aligned to the relationship between the **TAM-SHE** framework. See **Table 1.**

Table 1. Some articles relating TAM-SHE framework between 2020-2023

Item	Author	Title
1	Mina & Lashayo (2023)	Direct and indirect effects of smartphone use on academic performance of undergraduate students in Tanzania
2	Shanmugapriya et al. (2023)	Mobile technology acceptance among undergraduate nursing students instructed by blended learning at selected educational institutions in South India
3	Yu, T.K., & Chao, C.M. (2023)	Encouraging teacher participation in Professional Learning Communities: exploring the Facilitating or restricting factors that Influence collaborative activities
4	Fuchs (2022)	Using an extended technology acceptance model to determine students' behavioral intentions toward smartphone technology in the classroom
5	Badwelan & Bhaddad (2021)	Functional Requirements to Increase Acceptance of MLearning Applications among University Students in the Kingdom of Saudi Arabia (KSA)
6	Dafonte et al. (2021)	Smartphone use in university students: An opportunity for learning
7	Lin et al. (2021)	Utilizing Technology Acceptance Model for Influences of Smartphone Addiction on Behavioural Intention
8	Gyamfi (2021)	Influencing Factors of Students' Smartphones Use for Academic Purposes: A Developing Country's Perspective

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9	Nes et al. (2020)	Research protocol: Technology-supported guidance to increase flexibility, quality and efficiency in the clinical practicum of nursing education
10	Wismantoro et al. (2020)	Measuring the Interest of Smartphone Usage by Using Technology Acceptance Model Approach

Source: Own based on Web of Science database

So far, the study highlights a growing interest in the relationship between smartphone use in higher education and the Technology Acceptance Model (**TAM**) in the **post-COVID era**. The literature review underscores the significance of **TAM** in understanding students' behavioral intentions toward smartphone technology in the classroom. Despite the increasing number of publications related to both, **TAM** and smartphone use in higher education (**SHE**), only a fraction of them specifically addresses the intersection of **TAM** and smartphone technology in this context.

The findings from the search on the Web of Science database for the years 2020-2023 reveal notably, **10** documents in **TAM-SHE** specific intersection suggesting that while **TAM** is widely employed in studying technology adoption, its application to the context of smartphone use in higher education is still a relatively a niche area of research. These results highlight both the current state of research and the potential for further exploration in the **TAM-SHE** framework.

Researchers and educators may find value in delving deeper into the factors influencing the acceptance and adoption of smartphone technology in higher education, especially considering the unique challenges and opportunities posed by the **post-COVID era**.

Continued researh in this area can contribute valuable insights for the development of effective strategies to enhance the integration of smartphone technology in educational settings. Therefore, our research question is:

What is the technology acceptance model **(TMA)** for smartphone use in higher education **(SHE)** as an enhanced empirical framework and innovative tool in the **post-COVID era**?

3.3.Designing the conceptual framework

This section aims to determine a conceptual **TAM-SHE** framework (*ex-ante*) based on a qualitative study in this research, applying the Delphi Panel-Focus Group and Analytic Hierarchy Process (**AHP**) (Saaty, 2008). This procedure involved **three specialists**: **1** information technology expert, **1** information technology professor, and **1** university student to determine the

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main factors involved in the **TAM-SHE** as a conceptual construct framework. The results are displayed in **Table 2.**

Table 2. Delphi Panel-Focus Group and AHP. Identification of major factors and indicators of TAM-SHE as the underlying factor. Preliminary questionnaire.

Names suggested by 1 information technology professor (academic vision), and 1 university student (user vision)		Priorities suggested by 1 information technology expert, (expert vision)
Factors	***Indicators based on the perception of Likert Scale 1-7 (1. Strongly disagree; 2. Disagree; 3. Somewhat disagree; 4. Neither agree or disagree; 5. Somewhat agree; 6. Agree; 7. Strongly agree).***	**AHP Priorities (%) importance**
1. ATT	**N1.** I like my subjects better for the achievement of my learning when I use my smartphone.	0.39
	N2. The mobility in using my smartphone to achieve my learning is the most notable advantage.	0.31
	N3. Using my smartphone to achieve my learning goals is a smart choice.	0.30
	Total	**1.0**
2. EXP	**J1.** The experience of using my smartphone to achieve my learning is better than expected.	0.8
	J2. To achieve my learning goals, the level of service provided by my smartphone is better than expected.	0.12
	J3. Most of my expectations about the use of my smartphone to achieve my learning were positively confirmed.	0.08
	Total	**1.0**
3. LRS	**E1.** The results of my learning on my smartphone make me more collaborative.	0.52
	E2. The results of my smartphone's learning make me more pragmatic.	0.30
	E3. The results of my smartphone's learning make me more reflective.	0.18
	Total	**1.0**
4. MNG	**C1.** It is easy for me to schedule my classes through my smartphone.	0.44
	C2. Administering exams and receiving feedback on progress information from my teacher is easy through my smartphone.	0.30
	C3. . The administration of the content I access through my smartphone to achieve my learning motivates me to self-evaluate my progress.	0.26
	Total	**1.0**
5. MTV	**D1.** Using my smartphone, in my learning process motivates me to select and decide what and how to learn.	0.41
	D2. Using my smartphone, in my learning process motivates me to select and decide what and how to learn.	0.39
	D3. Using my smartphone in my learning process motivates me to be more perceptive of the environment and the consequences of my actions.	0.20
	Total	**1.0**
6. PEU	**K1.** Using my smartphone to achieve my learning is easy and flexible.	0.40
	K2. The interaction with my smartphone to achieve my learning is clear and understandable.	0.33

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	K3. The interaction with my smartphone to achieve my learning is clear and understandable.	0.27
	Total	**1.0**
7. PUS	**L1.** Accomplishing my learning with my smartphone improves my efficiency.	0.42
	L2. Accomplishing my learning with my smartphone allows me to accomplish tasks more quickly, saving time.	0.38
	L3. Accomplishing my learning with my smartphone improves my overall performance.	0.20
	Total	**1.0**
8. SFB	**G1,** The achievement of my learning through my smartphone is due to my intuition in its use.	0.58
	G2. The achievement of my learning through my smartphone is due to the security that its use inspires.	0.32
	G3. I achieved my learning through my smartphone because the ways to evaluate myself are simple and effective.	0.10
	Total	**1.0**
9. SQY	**I1.** The ways of evaluating the objectives, contents, activities, and available technological resources are consistent with the achievement of my learning through my smartphone.	0.62
	I2. The evaluation of acquired knowledge and skills vs. My initial expectations are notable as an achievement of my learning through my smartphone.	0.28
	I3. In general, the learning I achieve through my smartphone is of quality.	0.10
	Total	**1.0**
10. USI	**Q1**. I try to use my smartphone to achieve my learning goals whenever I can.	0.66
	Q2. I prefer the use of my smartphone to achieve my learning over any other option.	0.22
	Q3. I always recommend the use of smartphones to other people to achieve learning.	0.12
	Total	**1.0**
11.VCB	**H1.** Despite the advantages of using my smartphone to achieve my learning, the equipment is still expensive.	0.55
	H2. The service is still expensive despite the advantages of using my smartphone to achieve my learning.	0.33
	H3. The service is still expensive, despite the advantages of using my smartphone to achieve my learning.	0.12
	Total	**1.0**

Notes:
1. ATT. Student Attitude; **2. EXP.** Student Expectations; **3. LRS.** Student Learning Results; **4. MNG.** Student Self-Management; **5. MTV.** Student Motivation; **6.PEU.**Perceived Ease of Use; **7.PUS.** Perceived Usefulness; **8.SFB.** Student Achievements; **9. SQY.** Student Quality Perceptions; **10.USI.** Behavioral Intention; **11.VCB.** Student Cost-Benefit Perception

The technology acceptance model (**TAM**) is a theoretical framework that consists of perceived usefulness (**PUS**), perceived ease of use (**PEU**), attitude toward using (**ATT**), behavioral intention to use (**USI**), and actual system use. Here, actual system use is posed by the smartphone use in higher education (**SHE**) described such as student self-management **(MNG),** student learning results **(LRS),** student achievements perceptions **(SFB),** student cost-benefits perceptions **(VCB),** and student expectations **(EXP)** that help to understand and explain how students' acceptance and adoption of smartphone technology could be better achieved.

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Nowadays, after the **COVID-19** pandemic, the student motivation (**MTV**) and the student quality perceptions (**SQY**) are two factors that reinforce the **TAM** model.

The next step is the definition of each one of the factors related to the initial conceptual model as a result of **Delphi Panel-Focus Group** and **AHP**. These elements are known as the outer model in **PLS-SEM** too, and they describe the best relationship of how the factors are interacting for a better explanation of the **TAM-SHE** model, as follows:

3.3.1. Student Quality Perceptions (**SQY**) and Perceived Usefulness (**PUS**).

Alkhawaja et al. (2022) found that system student quality perceptions (**SQY**) indirectly influence e-learning system use through **PUS**. Similarly, Al-Debei (2014) identified information quality as a key predictor of **PUS**. Larmuseau (2018) highlighted the importance of perceived instructional quality and individual, social, and organizational factors in influencing acceptance and use. Hence, we proposed the following hypothesis:

H1: *"Higher **SQY** Higher **PUS**"*

3.3.2. Student Quality Perceptions (**SQY**) and Perceived Ease of Use (**PEU**).

The technology acceptance model (**TAM**) has been extended to explore students' intention to use online education platforms, with factors such as perceived system quality (**SQY**) and perceived interaction as perceived ease of use (**PEU**) being considered (Zhou et al., 2022). The attitude towards using cell phones is significantly being affected by perceived usefulness (**PEU**) and perceived ease of use (**PUS**). The attitude towards using cell phones is significantly being affected by perceived usefulness and perceived ease of use (Zogheib & Daniela). Hence, we proposed the following hypothesis:

H2: *"Higher **SQY** Higher **PEU**"*

3.3.3. Student Motivation (**MTV**) and Perceived Usefulness (**PUS**).

Smartphones can improve student motivation (**MTV**) levels during learning due to their interactive and collaborative nature, as well as their portability and ubiquity as perceived usefulness (**PUS**) (Matyokurehwa et al., 2020). The primary perceived benefits of smartphone

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use in learning are associated with students' motivation (**MTV**), and active participation in the learning process (Masadeh, 2021). Smartphone use motivates human-to-human interaction due to the perceived usefulness (**PUS**), and stimulate the creation and reinforcement of social networks, which can lead to better educational performance (Wang et al., 2023).Hence, we proposed the following hypothesis:

H3: *"Higher **MTV** Higher **PUS**"*

3.3.4. Student Motivation (**MTV**) and Perceived Ease of Use (**PEU**).

Morales-Rodríguez et al. (2020) highlighted the impact of emotions as motivations (**MTV**) on smartphone use, with the former finding a strong relationship between students' sentiments and their use of smartphones, and the latter identifying a link between smartphone addiction and emotional, cognitive, and educational dimensions. However, Camilleri & Camilleri (2019) found no significant relationship between **PEU** and students' enjoyment as motivation, in using educational apps. Sun & Gao (2019) found **PEU** did not directly influence students' intention to use mobile devices, suggesting that it was not predicted by intrinsic motivation (**MTV**). Hence, we proposed the following hypothesis:

H4: *"Higher **MTV** Low **PEU**"*

3.3.5. Perceived Usefulness (**PUS**) and Behavioral Intention (**USI**).

Students' **PUS** of cell phones influences their attitude towards using them, which in turn affects their **USI** to utilize cell phones more in their academic activities (Zogheib & Daniela, 2022). Baker-Eveleth,L. & Stone (2020) found that **PUS** significantly influenced satisfaction and **USI**. However, Tossell et al. (2015) found that students' perceptions of smartphones as educational tools can change over time, with initial positive views turning negative. Hamzah et al. (2020) confirmed the importance of **PUS** in predicting **USI,** focusing on the role of performance expectancy. Hence, we proposed the following hypothesis:

H5: "*Higher **PUS** Higher **USI**"*

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3.3.6. Perceived Ease of Use (**PEU**) and Student Attitude **(ATT**).

Rojas-Osorio&Alvarez-Risco (2019) found that **PEU** significantly influenced the intention to keep using a smartphone among Peruvian university students. Similarly, Ozbek et al.(2014) identified a positive influence of **PEU** on **ATT**. Smartphones have been found to aid learners develop positive **ATT** towards learning (Dzamesi et al., 2019). Hence, we proposed the following hypothesis:

H6: *"Higher **PEU** Higher **ATT**"*

3.3.7. Behavioral Intention (**USI**) and Student Self-Management **(MNG**).

The behavioral intention (**USI**) refers to the level to which an individual has made a deliberate decision to perform a certain behavior. In the context of education, studies have investigated factors that influence students' behavioral intention (**USI**) to use e-learning systems (Humida et al., 2022). The student self-management (**MNG**) of learning has a significant impact on **USI** to use smartphones for academic learning (Sambo et al., 2022). Besides, performance expectancy, effort expectancy, and self-management (**MNG**) of learning were important determinants of students' behavioral intention (**USI**) to use mobile learning technology (Hameed et al., 2022). Hence, we proposed the following hypothesis:

H7: "*Higher **USI** Higher **MNG**"*

3.3.8. Student Attitude **(ATT**) and Behavioral Intention (**USI**).

Fook et al. (2022) found that positive academic behavior mediates the relationship between mobile phone use and mobile learning intention. A study on university students' behavioral intention (**USI**) to use mobile learning confirmed the acceptability of the **TAM** to explain students' acceptance of mobile learning, emphasizing the role of attitude (**ATT**) in shaping behavioral intention (Sung et al., 2011). Research has shown that **ATT** towards cell phones positively affect behavioral intention, (**USI**) indicating that a positive **ATT** towards smartphones can influence the intention to use them for learning purposes (Zogheib & Daniela, 2022). Hence, we proposed the following hypothesis:

H8: *"Higher **USI** Higher **ATT**"*

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3.3.9. Behavioral Intention (**USI**) and Student Learning Results (**LRS**)

The impact of smartphone usage on student learning results (**LRS**) may depend on the students' major fields and their behavioral intention (**USI**) to use smartphones (Sunyoung & Yong, 2019). Parveen & Zamir (2020) found that performance expectancy, social influence, and facilitating conditions positively influence this intention (**USI**). Mtebe & Raisamo (2014) highlighted the role of beliefs and attitudes, and performance expectancy, effort expectancy, social influence, and facilitating conditions, respectively. The findings revealed that the distance learning students find it easier to use a smartphone in their learning activities and results (**LRS**) (Darko-Adjei, 2019). Hence, we proposed the following hypothesis:

H9: *"Higher **USI** Higher **LRS**"*

3.3.10. Behavioral Intention (**USI**) and Student Achievements (**SBF**)

Recent research indicates that behavioral intention (**USI**) to use smartphones wield a dual influence on students' academic success (**SBF**). Proper use, marked by convenience and accessibility, improves performance. Conversely, excessive smartphone usage has been correlated with diminished academic achievement, primarily due to distractions (Mejía-Trejo, 2021) and reduced time devoted to homework. The dichotomy underscores the need for a nuanced understanding of smartphone impact on student learning. (Huey & Giguere, 2023). Smartphone utilization negatively correlates with students' academic performance, suggesting no significant relationship between smartphone use and academic success (**SBF**) (Peteros et al., 2022). Hence, we proposed the following hypothesis:

H10: *"Higher **USI** Higher **SBF**"*

3.3.11. Behavioral Intention (**USI**) and Student Cost-Benefit Perception (**VCB**)

Mostafa (2023) identified price value (**VCB**) as significant predictor of intention to use a smart campus. Sun et al. (2018) found that students perceive **VCB** in interactive digital textbooks. Students are more likely to use smartphones as cost-benefit perception behavioral intention (**USI**) for quick communications, such as checking grades, messages, or due dates, rather than for academic tasks like reading or completing assignments (Baiyun et al. , 2023). Additionally, the

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ease and flexibility offered by mobile learning through smartphones and apps have been identified as appealing factors for students (Siew et al., 2017)

Hence, we proposed the following hypothesis:

H11: *"Higher **USI** Higher **VCB**"*

3.3.12. Behavioral Intention (**USI**) and Student Expectations (**EXP**)

This relationship, in the context of higher education, is a complex and multifaceted issue. While the search results provide insights into the prevalence and impact of smartphone use in higher education, they do not directly address the specific relationship between smartphone use and behavioral intention (**USI**) or student expectations (**EXP**). Tossell (2015) discovered that students' views on the educational utility of smartphones may evolve over time, shifting from initially optimistic expectations (**EXP**) to later becoming pessimistic. Feng et al. (2015) found that performance expectancy (**EXP**), positively influence the behavioral intention (**USI)**.

Hence, we proposed the following hypothesis:

H12: *"Higher **USI** Higher **EXP**"*

4. RESEARCH METHOD

This segment outlines the process of assembling and consolidating the datasets for subsequent data analysis, which was conducted in **three steps** as outlined below:

Step 1. Based on a previous context description, a qualitative study based on the Delphi Panel-Focus Group and Analytic Hierarchy Process (**AHP**) to determine the preliminary questionnaire **TMA-SHE** (*ex-ante*), gathering **three** specialists: **1** information technology expert, **1** information technology professor, and **1** university student to determine the main factors involved in the **TAM-SHE** as a conceptual construct framework. So far, this step has been resolved, concluding in **33 items** (**24 useful**) distributed in **11 factors**.

Step 2. It involves a literature review to elucidate the components and variables incorporated in the questionnaire proposed during the design phase. This review will be conducted prior to implementation and will encompass more than **523 students** from Mexican universities during the **second semester of 2023**.

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Step 3. After collecting all the questionnaire data and verifying their reliability through **Cronbach Alpha**, a quantitative study utilizing confirmatory factor analysis with partial least squares structural equation modeling (**PLS-SEM**) is employed. This analysis examines convergent, discriminant, and nomological validity for the finalized **TAM-SHE** framework.

4.1. Demographic data

Based on the results obtained from the frequency analysis of **523 subjects**, the most important data of the participants were: 18–29 years old (**84.3%**); male (**53.6%**), single (**91.4%**), high school (**87.3%**), with monthly income less than 10,000 Mexican pesos (**42.8%**). The results of the frequency demographic data analysis are exhibited in **Table 3**.

Table 3.Research sample demographic profile

Measure	Items	Frequency	Percentage
Age		39	8.8
	12-18	**29**	**5.5**
	18-29	**441**	**84.3**
	30-39	**37**	**7.1**
	40-49	**11**	**2.1**
	50-59	**3**	**0.6**
	60-69	**2**	**0.4**
Gender	**Male**	**234**	**46.4**
	Female	**270**	**53.6**
Marital Status	**Single**	**459**	**91.4**
	Married	**41**	**8.2**
Education Level	**High School**	**439**	**87.3**
	Master Degree	**43**	**8.5**
	Doctor Degree	**7**	**1.4**
Monthly Income (Mexican Pesos)	**<1,000**	**133**	**27.3**
	1,000-10,000	**209**	**42.8**
	10,000-20,000	**77**	**15.8**
	20,000-30,000	**20**	**4.1**
	30,000-40,000	**11**	**2.3**
	>40,000	**36**	**7.4**

Source: Own

4.2. Sampling based on PLS-SEM technique

The critical discussion for Confirmatory Factor Analysis (**CFA**) based on **PLS-SEM** applications' sample size technique involves how large a sample is needed to produce reliable results (Mejía-Trejo, 2018). This decision involves three aspects of framework complexity. According to Hair et al. (2019), the sampling frames could be addressed among:

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a. **Number of constructs.** Prior reviews indicate the average number of constructs per model is higher in **PLS-SEM** (Partial Least Squares-SEM, approximately **eight** constructs) compared to **CB-SEM** (Covariance-Based-SEM approximately **five** constructs)
b. **Number of indicators per construct.** Simultaneously, the number of indicators per construct is typically higher in **PLS-SEM** than in **CB-SEM**. In contrast, the **PLS-SEM** algorithm does not simultaneously compute all the framework relationships but instead uses separate ordinary least squares regressions to estimate the partial regression relationships.
c. **Number of observations per estimated parameter.** Finally, sampling adequacy for this research is based on the number of framework parameters. Minimum sample size of **N= 100 to 150** for conducting **SEM** (Tinsley & Tinsley, 1987; Anderson & Gerbing, 1988; Ding et al., 1995; Tabachnick & Fidell, 2001)**.** Some researchers consider an even larger sample size for **SEM,** for example, **N = 200** (Hoogland & Boomsma 1998; Boomsma & Hoogland, 2001; Kline, 2016). Simulation studies show that with normally distributed indicator variables and no missing data, a reasonable sample size for a simple **CFA** model is about **N = 150** (Muthén & Muthén, 2002). The rule of thumb for multi-group modeling is **100** cases/observations per group (Kline, 2016). Sample size is often considered in light of the number of observed variables. Bentler & Chou (1987) suggest a ratio as low as **5** cases per variable would be sufficient for normally distributed data when latent variables have multiple indicators. Following Hair et al. (2019) again, a basic rule of thumb for sample size is **10** times the number of arrows pointing at a construct, whether as a formative indicator to a construct or a structural path to an endogenous construct. The **PLS-SEM** algorithm obtains solutions when other methods do not converge or develop inadmissible solutions. In our case **33** indicators X **10** times = **330**, with a power analysis =**0.8**, alpha=**.05**, number of predictors=**11** effect size= **medium** the resulting sample size= **139** (**See Table 4**)**.**

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Table 4. Sample size based on new rule-of-thumb required to Test the Hypothesis that population multiple correlations equals zero with the power of 0.80 (Alpha=.05)

Number of predictors	Sampled sizes based on power analysis		
	Effect size		
	Small	Medium	Large
1	**400**	**53**	**23**
2	**475**	**63**	**27**
3	**545**	**73**	**31**
4	**610**	**81**	**35**
5	**670**	**89**	**38**
6	**725**	**97**	**41**
7	**775**	**103**	**44**
8	**820**	**109**	**47**
9	**860**	**115**	**49**
10	**895**	**119**	**51**
15	**1045**	**139**	**60**
20	**1195**	**159**	**68**
30	**1495**	**199**	**85**
40	**1795**	**239**	**103**

Source: Belsley (1991), p.503

The **523>139** Mexican online university students as main users of **TAM-SHE** sample fulfill this condition widely**.**

4.3. Data collection

The *"virtual snowball sampling"* method was used in this research; it is a method to recruit participants to access representative samples of interconnected human networks involving consumers with an online user experience. Also, they are very sensitive respondents due to the closed **TMA-SHE**. Participants (initially **680**; finally, **523**) were asked to answer the questionnaire created in **Table 2** to remind them of their perceptions. They were also provided with a brief description of the concepts dealt with before answering the survey.

Participation was voluntary, and confidential; no rewards were provided for participants; it was sent the survey questionnaire via Google Forms from **June 06 to December 06, 2023**.

Therefore, the sample represents online students' perceptions of technology acceptance model (**TMA**) for smartphone use in higher education (**SHE**).

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4.4. The survey instrument

The final survey resulted from the Delphi Panel-focus Group and **AHP** techniques among **three specialists**: **1** information technology expert, **1** information technology professor, and **1** university student related to **TAM-SHE** conceptual framework**.** The main question was proposed as a **reflective mode**, with the sentence: *" How do you perceive the following issues in Likert Scale 1-7 (1. Strongly disagree; 2. Disagree; 3. Somewhat disagree; 4. Neither agree or disagree; 5. Somewhat agree; 6. Agree; 7. Strongly agree)".* The results were posed for each pair of members in **3 rounds** (**3** subjects in **2** combinations without repetition) according to CombCal (2023). We weighed each round using AHP, and the names were suggested by 1 information technology professor (academic vision) and **1** university student (user vision). Priorities suggested by **1** information technology expert, (expert vision), obtaining the preliminary questionnaire with **11** factors and **33** items (**24 useful**).. See **Table 2.**

The preliminary questionnaire was probed regarding the **Cronbach Alpha** reliability (Mejía-Trejo, 2017), and with the use of confirmatory factor analysis (**CFA**) using partial least-squares structural equation modeling **(PLS-SEM)** with **SmartPLS 4.0.9.6** testing convergent, discriminant, and nomological validity, ensuring that the instrument measures what it intends to measure.

5. RESULTS

This section introduces the **Cronbach Alpha** results for reliability an de results of the **confirmatory factor analysis (CFA)** using partial least-squares structural equation modeling (**PLS-SEM)** with **SmartPLS 4.0.9.6** testing convergent, discriminant, and nomological validity, among **33 items** and **11 factors.**

5.1. Cronbach alpha, Reliability test

Using **IBM-SPSS 29** on the results of the preliminary questionnaire within **523** subjects data in **33 items** in **11 factors** and based on Hair et al. (2019), we attained the **Cronbach's Alpha** reliability showed in **Table 5.**

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Table 5. Reliability statistics

Reliability Statistics

Cronbach's Alpha	N of Items
.974	33

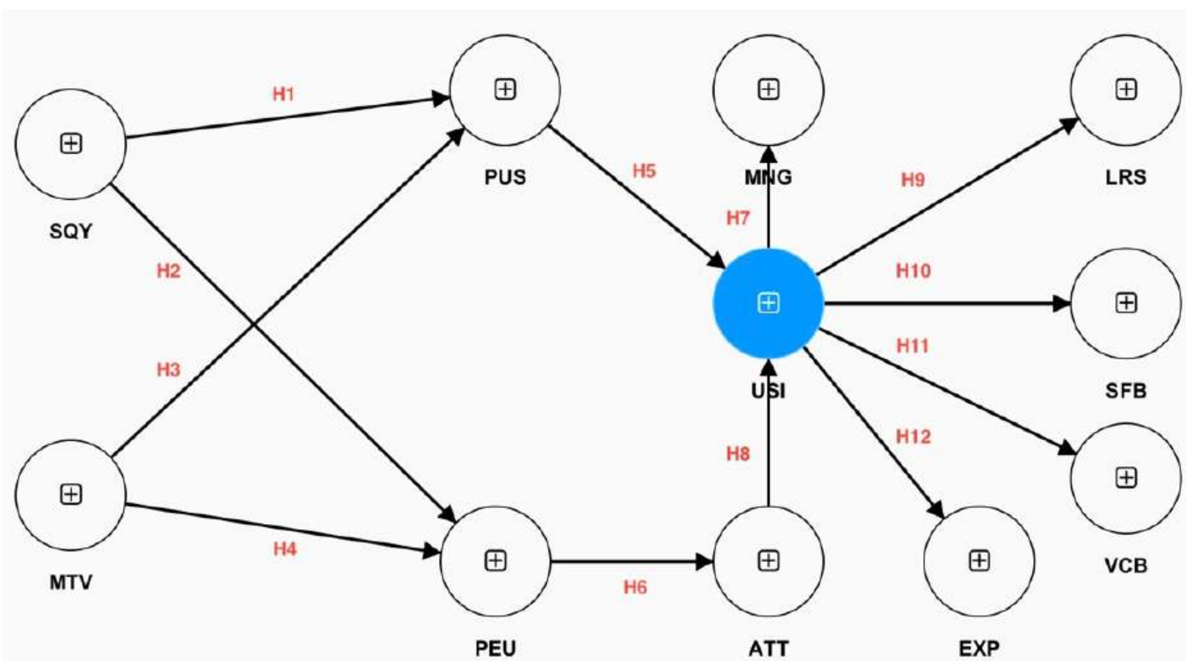
Source: Own using IBM-SPSS 29

Despite the high value in reliability statistics (**0.974**) among the **33 items** in **11 factors**, these results show high collinearity to solve with the **PLS-SEM** test.

5.2. Confirmatory factor analysis (CFA)

Thereby, according to the factors and indicators of **TAM-SHE** as initial questionnaire (*ex-ante*) model shown in **Figure 1** are related as follows:

Figure 1. The TAM-SHE as *ex-ante* model



Notes:
1. ATT. Student Attitude; **2. EXP**. Student Expectations; **3. LRS.** Student Learning Results; **4. MNG.** Student Self-Management; **5. MTV.** Student Motivation; **6.PEU.**Perceived Ease of Use**; 7.PUS.** Perceived Usefulness; **8.SFB.** Student Achievements; **9. SQY.** Student Quality Perceptions; **10.USI.** Behavioral Intention; **11.VCB**. Student Cost-Benefit Perception

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5.3. The CFA/PLS-SEM analysis technique

PLS-SEM (Partial Least Square Structural Equation Modeling) (Wold, 1982; Lohmoller, 1989) is an estimation method based on components, distinguishing itself from conventional covariance-based structural equation modeling (**CB-SEM**). Unlike the latter, **PLS-SEM** does not fit a common factor model to the data, opting for a composite model instead (Henseler et al. 2014; Rigdon et al., 2017). By doing this, it aims to maximize the explained variance.

The **PLS-SEM** consists of two distinct components: the *measurement and structural models*. The outer or *measurement model* depicts the connections between the observed data and the hidden variables, while the inner or *structural model* portrays the associations between these latent variables An iterative algorithm solves the **SEM** by alternating between estimating the latent variables using the *measurement and structural models*, explaining the name *"partial."* The *measurement model* estimates the latent variables as a weighted combination of their observed counterparts. Meanwhile, the *structural model* estimates the latent variables through either simple or multiple linear regression based on the latent variables previously estimated by the *measurement model.* This process iterates until convergence is achieved (Henseler et al. 2014; Dijkstra & Henseler, 2015; Rigdon et al., 2017).

PLS-SEM is an emerging approach to statistical data analysis, this technique, though recently developed, is experiencing a rapid surge in popularity and finds applications in diverse fields. It has captured the attention of scholars employing diverse methodologies, establishing itself as a dynamic and continually advancing method (Methodspace, 2023).

In the contemporary landscape, professionals ranging from corporate and public administration managers to academics and researchers can now access substantial datasets for informed decision-making and exploring novel insights (Becker et al., 2023). **PLS-SEM** is still considered preferable (over covariance-based structural equation modeling) when it is unknown whether the data's nature is a common factor or composite-based (Sarstedt et al., 2016).

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5.3.1. The measurement model internal consistency reliability, significance, and variance assessment as convergent validity

They were computed according to **SmartPLS 4.0.9.6** software, with values per factor, of **Cronbach´s alpha** (>=0.7) (Hair et al., 2023), of **rho_A** index (>=0.7) (Dijkstra & Hanseler, 2015), of composite reliability index (**CRI**) (>=0.7), and average extracted variance index (**AVE**) (>=0.5) (Hair et al., 2023). The indicator's outer loadings should be **>0.70**. The indicators with values between **0.40-0.70** as outer loadings are for removal only. Such action increases **CRI** and above the suggested threshold value (Hair et al., 2023). Convergent validity is measured as **AVE**, which is the grand mean value of the squared loadings of the indicators associated with the construct (Fornell & Larcker, 1981). Therefore, we had to remove **J3, E1, K2, L3, I2** and **Q3** because of their collinearity issues and **N1, D3** to adjust **AVE** and **H3** for the measurement model to achieve all the indexes mentioned above. Hence, the **TME-SHE** model fulfills the reliability and convergence validity required. See **Table 6.**

Table 6. The TAM-SHE measurement model internal consistency reliability, significance, and variance assessment as convergent validity. Final questionnaire (*ex-post*) with 11 factors and 33 items (24 useful).

Items	**1.ATT.** Cronbach's alpha (>=0.7)= **0.832**; Dijkstra–Henseler's rho (>=0.7)= **0.849** CRI (>=0.7= **0.922**; AVE (>=05)=**0.855**	**Outer loading**	***p* Value**
1	**N1.** I like my subjects better for the achievement of my learning when I use my smartphone.	**Removed. Problems with AVE**	
2	**N2.** The mobility in using my smartphone to achieve my learning is the most notable advantage.	**0.912**	**0.000**
3	**N3.** Using my smartphone to achieve my learning goals is a smart choice.	**0.938**	**0.000**
	2.EXP Cronbach's alpha (>=0.7)= **0.890**. ; Dijkstra–Henseler's rho (>=0.7)= **0.902**; CRI (>=0.7= **0.948**; AVE (>=05)= **0.900**	**Outer loading**	***p* Value**
4	**J1.** The experience of using my smartphone to achieve my learning is better than expected.	**0.956**	**0.000**
5	**J2.** To achieve my learning goals, the level of service provided by my smartphone is better than expected.	**0.942**	**0.000**
6	**J3.** Most of my expectations about the use of my smartphone to achieve my learning were positively confirmed.	**Removed. Problems with collinearity**	
	3.LRS. Cronbach's alpha (>=0.7)= **0.859** ; Dijkstra–Henseler's rho (>=0.7)= **0.859** ;CRI (>=0.7= **0.934**; AVE (>=05)= **0.876**	**Outer loading**	***p* Value**
7	**E1.** The results of my learning on my smartphone make me more collaborative.	**Removed. Problems with collinearity**	
8	**E2.** The results of my smartphone's learning make me more pragmatic.	**0.934**	**0.000**
9	**E3.** The results of my smartphone's learning make me more reflective.	**0.938**	**0.000**
	4.MNG. Cronbach's alpha (>=0.7)= **0.829** ; Dijkstra–Henseler's rho (>=0.7)= **0.889** ;CRI (>=0.7= **0.895** ; AVE (>=05)= **0.742**	**Outer loading**	***p* Value**

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10	**C1.** It is easy for me to schedule my classes through my smartphone.	**0.762**	**0.000**
11	**C2.** Administering exams and receiving feedback on progress information from my teacher is easy through my smartphone.	**0.904**	**0.000**
12	**C3.** . The administration of the content I access through my smartphone to achieve my learning motivates me to self-evaluate my progress.	**0.910**	**0.000**
	5.MTV. Cronbach's alpha (>=0.7)=**0.779**. ; Dijkstra–Henseler's rho (>=0.7)=**0.781** ;CRI (>=0.7= **0.901**; AVE (>=05)= **0.819**	**Outer loading**	***p* Value**
13	**D1.** Using my smartphone, in my learning process motivates me to select and decide what and how to learn.	**0.911**	**0.000**
14	**D2.** Using my smartphone in my learning process motivates me to always be connected to the internet at all times and places.	**0.899**	**0.000**
15	**D3.** Using my smartphone in my learning process motivates me to be more perceptive of the environment and the consequences of my actions.	**Removed. Problems with AVE**	
	6.PEU. Cronbach's alpha (>=0.7)= **0.851** ; Dijkstra–Henseler's rho (>=0.7)= **0.867**; CRI (>=0.7= **0.930** ; AVE (>=05)= **0.870**	**Outer loading**	***p* Value**
16	**K1.** Using my smartphone to achieve my learning is easy and flexible.	**0.944**	**0.000**
17	**K2.** The interaction with my smartphone to achieve my learning is clear and understandable.	**Removed. Problems with collinearity**	
18	**K3.** The interaction with my smartphone to achieve my learning is clear and understandable.	**0.921**	**0.000**
	7.PUS. Cronbach's alpha (>=0.7)= **0.851** ; Dijkstra–Henseler's rho (>=0.7)= **0.855** ;CRI (>=0.7= **0.931** ; AVE (>=05)= **0.870**	**Outer loading**	***p* Value**
19	**L1.** Accomplishing my learning with my smartphone improves my efficiency.	**0.938**	**0.000**
20	**L2.** Accomplishing my learning with my smartphone allows me to accomplish tasks more quickly, saving time.	**0.927**	**0.000**
21	**L3.** Accomplishing my learning with my smartphone improves my overall performance.	**Removed. Problems with collinearity**	
	8.SFB. Cronbach's alpha (>=0.7)= **0.886** ; Dijkstra–Henseler's rho (>=0.7)= **0.889** ;CRI (>=0.7= **0.929**; AVE (>=05)= **0.814**	**Outer loading**	***p* Value**
22	**G1,** The achievement of my learning through my smartphone is due to my intuition in its use.	**0.891**	**0.000**
23	**G2.** The achievement of my learning through my smartphone is due to the security that its use inspires.	**0.924**	**0.000**
24	**G3.** I achieved my learning through my smartphone because the ways to evaluate myself are simple and effective.	**0.891**	**0.000**
	9.SQY. Cronbach's alpha (>=0.7)= **0.885** ; Dijkstra–Henseler's rho (>=0.7)= **0.886** ;CRI (>=0.7= **0.945**; AVE (>=05)= **0.897**	**Outer loading**	***p* Value**
25	**I1.** The ways of evaluating the objectives, contents, activities, and available technological resources are consistent with the achievement of my learning through my smartphone.	**0.945**	**0.000**
26	**I2.** The evaluation of acquired knowledge and skills vs. My initial expectations are notable as an achievement of my learning through my smartphone.	**Removed. Problems with collinearity**	
27	**I3.** In general, the learning I achieve through my smartphone is of quality.	**0.949**	**0.000**
	10.USI. Cronbach's alpha (>=0.7)= **0.834** ; Dijkstra–Henseler's rho (>=0.7)= **0.844** ;CRI (>=0.7= **0.923**; AVE (>=05)= **0.857**	**Outer loading**	***p* Value**
28	**Q1**. I try to use my smartphone to achieve my learning goals whenever I can.	**0.936**	**0.000**
29	**Q2.** I prefer the use of my smartphone to achieve my learning over any other option.	**0.916**	**0.000**
30	**Q3.** I always recommend the use of smartphones to other people to achieve learning.	**Removed. Problems with collinearity**	

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	11.VCB. Cronbach's alpha (>=0.7)= **0.898** ; Dijkstra–Henseler's rho (>=0.7)= **0.902**;CRI (>=0.7= **0.952**; AVE (>=05)= **0.908**	**Outer loading**	***p* Value**
31	**H1.** Despite the advantages of using my smartphone to achieve my learning, the equipment is still expensive.	**0.949**	**0.000**
32	**H2.** The service is still expensive despite the advantages of using my smartphone to achieve my learning.	**0.956**	**0.000**
33	**H3.** The service is still expensive, despite the advantages of using my smartphone to achieve my learning.	**Removed. Problems with the measurement model**	

Notes:

- **1.ATT.** Student Attitude; **2. EXP**. Student Expectations; **3. LRS.** Student Learning Results; **4. MNG.** Student Self-Management; **5. MTV.** Student Motivation; **6.PEU.**Perceived Ease of Use**; 7.PUS.** Perceived Usefulness; **8.SFB.** Student Achievements; **9. SQY.** Student Quality Perceptions; **10.USI.** Behavioral Intention; **11.VCB**. Student Cost-Benefit Perception
- **CRI.** Composite Reliability Index. Values **0-1**.
- **rho_A**. Values between **0.6-0.7** are acceptable in exploratory research, **0.7-0.9** reflect satisfactory to good results (Hair et al., 2019). **Values >0.95** suggest that the indicators could be measuring the same phenomenon and they are semantically redundant (Hair et al., 2019; Drolet & Morrison, 2001) with a potential common bias, this is the variation is from the instrument not by respondents (Straub et al., 2004).
- **AVE.** Average Variance Extracted Index**.>0.5** suggests that more than 50% of the construct represents items variance (Fornell & Larcker, 1981).
- Indicators are according to Likert Scale **1-7** (1. Strongly disagree; 2. Disagree; 3. Somewhat disagree; 4. Neither agree or disagree; 5. Somewhat agree; 6. Agree; 7. Strongly agree). This type of scale provides a balance between the respondents' complexity and the ease of analysis of the information (Hair et al., 2019)

*Values are kept because they are close to 0.7 and important for the final model.
Source: Own using **SmartPLS 4.0.9.6**

5.3.2. The TAM-SHE measurement model discriminant validity

It was computed with **SMARTPLS version 4.0.9.6**. software. It points to if an underlying factor is measuring a different construct and the degree to which indicators show an example of the target construct. It was calculated according to the traditional discriminant validity assessment method, which requires all relationships between constructs to be less than the lowest of the **AVE's** square root values (Fornell & Larcker, 1981). **See Table 7**.

Table 7. TAM-SHE measurement model discriminant and convergent validity

Fornell & Larcker Criteria (Diagonal= Root Square -AVE-) for discriminant validity HTMT Criteria Ratio<= 0.85<=0.90 for convergent validity											
Factors	**ATT**	**EXP**	**LRS**	**MNG**	**MTV**	**PEU**	**PUS**	**SFB**	**SQY**	**USI**	**VCB**
ATT	0.925	0.814	0.705	0.626	0.814	0.827	0.867	0.809	0.803	0.751	0.248
EXP	0.704	0.949	0.802	0.707	0.835	0.819	0.875	0.832	0.890	0.792	0.267
LRS	0.600	0.700	0.936	0.745	0.895	0.671	0.759	0.812	0.811	0.747	0.277
MNG	0.541	0.627	0.652	0.861	0.819	0.636	0.721	0.680	0.705	0.679	0.252
MTV	0.659	0.697	0.734	0.689	0.905	0.782	0.852	0.880	0.814	0.774	0.305
PEU	0.702	0.717	0.579	0.553	0.640	0.933	0.880	0.764	0.764	0.699	0.223
PUS	0.736	0.764	0.650	0.622	0.695	0.752	0.933	0.814	0.852	0.794	0.252

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SFB	0.699	0.738	0.708	0.608	0.731	0.669	0.708	0.902	0.842	0.734	0.291
SQY	0.696	0.791	0.707	0.625	0.678	0.668	0.742	0.746	0.947	0.810	0.310
USI	0.636	0.688	0.635	0.588	0.630	0.597	0.673	0.636	0.698	0.926	0.396
VCB	0.215	0.240	0.243	0.226	0.256	0.195	0.220	0.258	0.276	0.343	0.953

Notes:
HTMT. It ensures that different constructs capture different concepts. The cut-off value is **0.90** if the constructs are conceptually similar); a more conservative cut-off value is **0.85** (Henseler et al., 2015). Bootstrapping ensures that **HTMT** results are statistically significantly different from **1.0** because cut-off values have a high likelihood of falsely rejecting discriminant validity and are very conservative (i.e., Type II error) (Franke & Sarstedt, 2019)
Source: Own using **SmartPLS 4.0.9.6**

It includes the **HeteroTrait-MonoTrait** (**HTMT**) of the relationship criterion as a complement to evaluate discriminant validity. An estimate of what the true correlation between two constructs would be if they were perfectly measured is represented through the **HTMT** approach is (i.e., when they are perfectly reliable **HTMT<=0.85<=0.90**) (Henseler et al., 2015; Hair et al., 2023). Hence, the framework fulfills the discriminant validity.

5.3.3.The significance of the structural model relationships

Path coefficients are the hypothesized relationship among the constructs. They are ranged in standardized values between $\mathbf{-1}$ **and** $\mathbf{1}$(strongly negative or strongly positive). Values close to **0** are weak relationships. The ***p*-values** and the $\boldsymbol{f^2}$ effect sizes dictate the significance of path coefficients used on bootstrapping. It produces a sample distribution approaching the normal distribution; the result is used to establish critical ***t-values*** (Hair et al., 2019), and subsequently, the ***p-values*** to discuss the practical significance (Kraemer et al., 2003). Besides, to modify research conclusions, practical significance involves the magnitude of the observed effect and if it is enough. Therefore, a statistically significant relationship may not be practically significant. Also, some path coefficients might be a very small effect size but are significant; hence, they are essential to drawing appropriate conclusions. There is no consensus, so judgments on the practical significance rely on experts' considerations about measuring practical significance (Kraemer et al., 2003). This way, the significance of the structural model relationships is proved according to the hypotheses following **Figure 2.** Observe the reflective mode of the Behavioral Intention (**USI**) to explain the **TAM** actual system use through student self-management (**MNG**), student learning

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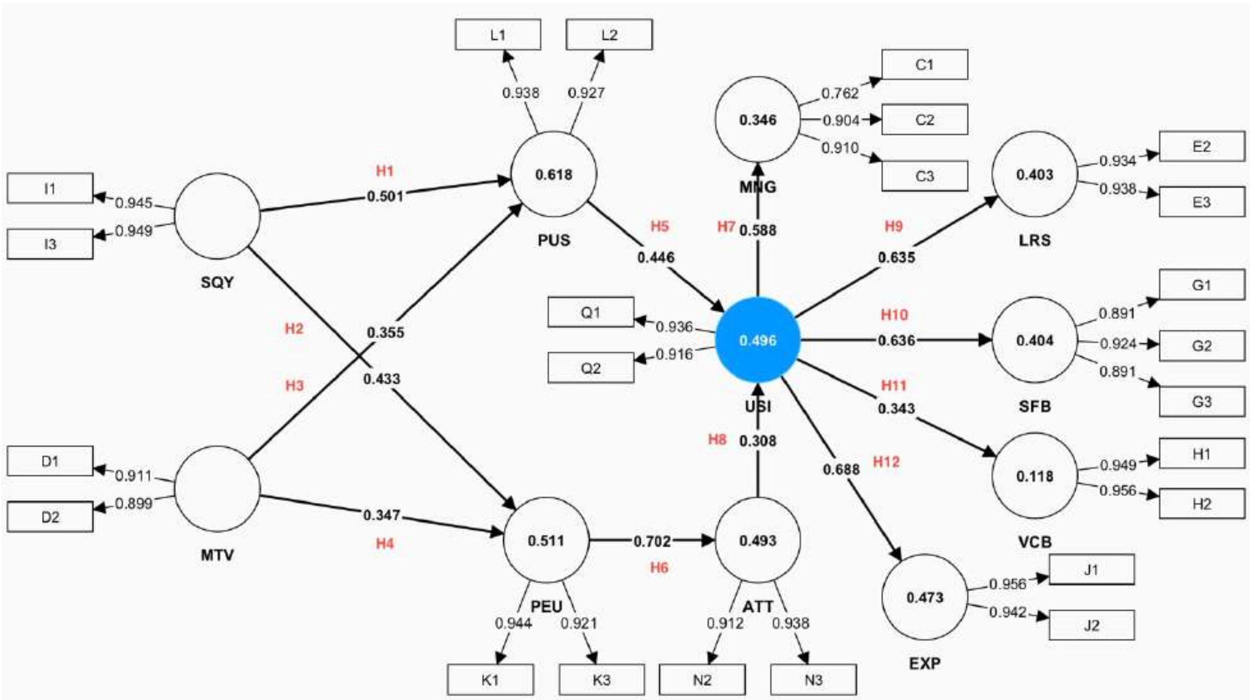
results (**LRS**), student achievements perceptions (**SFB**), student cost-benefits perceptions (**VCB**), and student expectations (**EXP**).

Figure 2. The TAM-SAHE Framework proposal for path coefficients, coefficient of determination (R^2) and hypotheses



Notes: **1.ATT.** Student Attitude; **2. EXP**. Student Expectations; **3. LRS.** Student Learning Results; **4. MNG.** Student Self-Management; **5. MTV.** Student Motivation; **6.PEU.**Perceived Ease of Use**; 7.PUS.** Perceived Usefulness; **8.SFB.** Student Achievements; **9. SQY.** Student Quality Perceptions; **10.USI.** Behavioral Intention; **11.VCB**. Student Cost-Benefit Perception
Source: Own using **SmartPLS 4.0.9.6**

5.3.4. TMA-SHE Model ́s explanatory power

The coefficient of determination explained variance, or R^2 value, is an essential critical measure in **PLS-SEM** because it measures the model's explanatory power. By each endogenous construct, R^2 measures the proportion of variance explained. In our case, the behavioral intention (**USI**) factor with an R^2 of **0.496** (see **Figure 2**) means that **49.6%** of its variation is explained by all the constructs that point to **USI**. Threshold values are not provided because they depend on the model's complexity and the subject matter.

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Thereby, the adjusted $\boldsymbol{R^2}$ criterion, is a good practice to consider because it adjusts the $\boldsymbol{R^2}$ value based on the model size (James et al., 2013). A specific exogenous underlying factor can be assessed if it has a substantial impact on the endogenous ones, using the $\boldsymbol{f^2}$ effect size (Cohen, 1988).

It measures if the exogenous construct has a substantial impact on the endogenous one. Thresholds $\boldsymbol{f^2}$ effect size values: **<0.02** represents no effect; **0.02–0.15** for small effect size; **0.15-0.35** for a medium-sized effect**;>0.35** a large effect size was proposed by Cohen (1988). See **Table 8.**

Table 8. TAM-SHE Structural Measurement Model and Hypotheses tests

Hypotheses	Paths	Path [*t-value; p-value*]	Result	5%-95% Confidence Interval	Interval Result (Crossing 0?)	f^2 Effect Size	
						(0.02<=; 0.15<=0.35)	Effect (Small; Medium; Large)
***H1**: "Higher SQY Higher PUS"*	**SQY -> PUS**	0.501 [12.611; 0.000]	**Accepted**	[0.432; 0.565]	No	0.356	**Large**
H2: "Higher SQY Higher PEU"	**SQY-> PEU**	0.433 [9.313; 0.000]	**Accepted**	[0.356; 0.510]	No	0.207	**Medium**
H3: "Higher MTV Higher PUS"	**MTV-> PUS**	0.355 [8.521; 0.000]	**Accepted**	[0.287; 0.425]	No	0.179	**Medium**
H4: "Higher MTV Low PEU"	**MTV-> PEU**	0.347 [7.074; 0.000]	**Rejected**	[0.265; 0.427]	No	0.133	**Small**
H5: "Higher PUS Higher USI"	**PUS-> USI**	0.446 [8.352; 0.000]	**Accepted**	[0.355; 0.532]	No	0.181	**Medium**
H6: "Higher PEU Higher ATT"	**PEU-> ATT**	0.702 [23.598; 0.000]	**Accepted**	[0.651; 0.749]	No	0.974	**Large**
H7: "Higher USI Higher MNG"	**USI -> MNG**	0.588 [19.794; 0.000]	**Accepted**	[0.539; 0.637]	No	0.530	**Large**
H8: "Higher ATT Higher USI"	**ATT-> USI**	0.308 [5.903; 0.000]	**Accepted**	[0.222; 0.395]	No	0.086	**Small**
H9: "Higher USI Higher LRS"	**USI-> LRS**	0.635 [21.602; 0.000]	**Accepted**	[0.585; 0.681]	No	0.676	**Large**

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H10:* *“Higher USI Higher SFB”	**USI-> SFB**	0.636 [19.912; 0.020]	**Accepted**	[0.582; 0.686]	No	0.678		**Large**
H11:* *“Higher USI Higher VCB”	**USI-> VCB**	0.343 [7.584; 0.000]	**Accepted**	[0.269; 0.419]	No	0.134		**Small**
H12:* *“Higher USI Higher EXP”	**USI-> EXP**	0.688 [26.315; 0.000]	**Accepted**	[0.643; 0.729]	No	0.898		**Large**
Q^2 Predict Model PLS-SEM with LM								
Independent Items	**Q^2>0**	**PLS-SEM RMSE**	**PLS-SEM MAE**	**LM-RMSE**	**LM-MAE**	**PLS-SEM - LM RMSE**	**PLS-SEM Prediction Error Skewness**	**Result**
C1	0.141	1.835	1.541	1.793	1.462	0.042	-0.548	**Highly predictive model**
C2	0.246	1.543	1.302	1.416	1.125	0.127	-0.415	
C3	0.331	1.303	1.061	1.007	0.777	0.296	-0.369	
E2	0.358	1.255	1.015	1.027	0.780	0.228	-0.402	
E3	0.340	1.340	1.092	1.152	0.853	0.188	-0.439	
G1	0.323	1.297	1.009	1.111	0.806	0.186	-0.913	
G2	0.347	1.335	1.066	1.128	0.835	0.207	-0.724	
G3	0.338	1.318	1.058	1.105	0.813	0.213	-0.644	
H1	0.065	1.599	1.335	1.599	1.321	0	-0.340	
H2	0.060	1.611	1.338	1.616	1.328	-0.005	-0.341	
J1	0.406	1.237	1.003	0.990	0.721	0.247	-0.502	
J2	0.397	1.217	0.977	0.996	0.736	0.221	-0.606	

Notes:

- **NA.** Not Applicable
- One-tailed ***t-values*** and ***p-values*** in parentheses; bootstrapping 95% confidence intervals (based on n= 5000 subsamples) **SRMR**: standardized root mean squared residual; **dULS**: unweighted least squares discrepancy; **dG**: geodesic discrepancy; HI99: bootstrap-based99% percentiles.
- $\boldsymbol{f^2}$.Effect size. 0.02, 0.15, and 0.35 are interpreted as small, medium, and large (Cohen, 1988)
- $\boldsymbol{R^2}$. Coefficients of determination represent the amount of explained variance of the endogenous constructs in the structural model. Therefore, values of 0.25, 0.50, 0.75 for target constructs are considered as weak, medium, and substantial, respectively (Hair et al. 2019)
- **SRMR**. The Standardized Root Mean Square Residuals are a common fit measure for CB-SEM (Henseler et al., 2015). Detection is also used for misspecification of **PLS-SEM** models (Henseler et al., 2014). Besides, it includes the following fit measures: squared Euclidean distance (**dULS**) and the geodesic distance (**dG**) (Dijkstra & Henseler, 2015)
- $\boldsymbol{Q^2}$ Predictive Indicator must be **>0** in an independent variable; **MAE.** Mean Absolute Error; **RMSE**. Root Mean Squared Error. If prediction errors are highly symmetrically distributed, use **RMSE; if not, use MAE.**
  In our case, the skewness is based on **RMSE,** where only **2/38** indicators were asymmetrically distributed. Thereby, the **SMA-PDP is a highly predictive model** (Shmueli et al. 2016)

Source: Own using **SmartPLS 4.0.9.6**

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6. DISCUSSION

We posed two approaches, with theoretical and practical implications as follows:

6.1.Theoretical implications

The theoretical contribution of this research approach is multi-faceted, combining all the elements mentioned above with qualitative and quantitative methods to develop and validate a questionnaire-related technology acceptance model (**TAM**) for smartphone use in higher education (**SHE**). Here, as a component of **TAM,** the actual system use is posed by the smartphone use in higher education (**SHE**) described such as student self-management **(MNG),** student learning results **(LRS),** student achievements perceptions **(SFB),** student cost-benefits perceptions **(VCB),** and student expectations **(EXP)** that help to understand and explain how students' acceptance and adoption of smartphone technology could be better achieved. The **post-COVID-19** pandemic era demands an analysis of how the new student motivation (**MTV**) and student quality perceptions (**SQY**) interact with the technology acceptance model (**TAM**). Hence, the main theoretical contributions are listed as follows:

- As we saw, **11 (eleven) hypotheses** were approved. The final **TAM-SHE** empirical framework is a highly predictive model **(Q^2 Predict Model PLS-SEM with LM**, see **Table 12**)
- The result of rejection was for ***H4:*** *"Higher MTV Low* ***PEU,"*** where a positive correlation exists, although its effect size is **small**. **D1**, **D2** (**MTV**), **K1**, and **K3** (**PEU**) collectively contribute to the motivations and perceptions of using smartphones in the learning process. However, their impact on the use of smartphones in higher education may be relatively modest due to several factors:
    a. **Varied Student Preferences.** The motivations outlined in **D1** and **D2** are subjective and may vary among students. While some may be highly motivated by the autonomy to shape their learning experience, others may prioritize different aspects of smartphone use. The effectiveness of **K1** and **K3** is also subject to individual preferences and technical proficiency.

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b. **Institutional Infrastructure.** The use of smartphones in higher education is often constrained by the existing institutional infrastructure. If universities lack the necessary technological support or have stringent policies, the impact of individual motivations and perceived ease of use may be limited.
c. **Educational pedagogy.** The nature of educational pedagogy in higher education can influence the incorporation of smartphones. Some courses may require a more traditional approach, limiting the extent to which smartphones are integrated into the learning process.
d. **Digital literacy.** The ease and flexibility perceived in **K1** and the clarity of interaction in **K3** rely heavily on students' digital literacy. If students are not adequately familiar with smartphone technologies, the perceived ease of use may not translate into effective utilization.
e. **Balancing autonomy and structure.** While **D1** emphasizes autonomy, there is also a need for structured learning in higher education. Striking a balance between self-directed learning and adherence to academic guidelines is essential.
f. **Potential distractions.** The constant connectivity highlighted in **D2** may introduce challenges such as potential distractions. In a higher education setting, where focused learning is crucial, the perceived need for constant internet access might need to be carefully managed.
g. **Faculty and institutional policies.** The willingness of faculty to integrate smartphones into the learning process and the policies set by educational institutions play a crucial role. Resistance from educators or restrictive policies may hinder the widespread adoption of smartphones.
h. **Security and privacy concerns.** Higher education institutions often have stringent security and privacy requirements. Data security and privacy concerns may limit how much smartphones are fully embraced.

- Another result highlighted is **H8:** *"Higher **ATT** Higher **USI,**"* whose effect is small despite being approved**. N2, N3** (**ATT**), **Q1**, and **Q2** (**USI**) collectively highlight the advantages and personal preferences of using smartphones for learning. While these factors can contribute

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positively to the use of smartphones in higher education, their impact may be relatively small due to various considerations:

a. **Institutional policies.** Higher education institutions often have established policies that may govern using smartphones in classrooms or for learning purposes. Institutional guidelines can either facilitate or restrict students' use of their smartphones for educational purposes.
b. **Course requirements.** The nature of different courses may impact the feasibility of using smartphones for learning. Some courses may require specialized software, equipment, or platforms that are not easily compatible with smartphones, limiting their effectiveness.
c. **Technological infrastructure.** The success of mobile learning is contingent on robust technological infrastructure, including internet connectivity and compatibility with various devices. Institutions with limited technological resources may need help in fully accommodating the mobility aspect highlighted in **N2**.
d. **Educational pedagogy.** The approach to teaching and learning in higher education varies. Some educators may be more traditional in their methods, while others may actively embrace technology. The extent to which smartphones are integrated into the learning process depends on the prevailing educational pedagogy.
e. **Student preferences.** While **Q1** and **Q2** express individual preferences for using smartphones in learning, the student body may have diverse preferences. The impact of these personal preferences may be limited by the varying needs and habits of students.
f. **Digital literacy.** The effective use of smartphones for learning requires a certain level of digital literacy. The impact may be restricted if students or faculty members need to learn to use smartphones for educational purposes.
g. **Alternative learning resources**. Higher education institutions often provide various resources, including libraries, computer labs, and other facilities. Depending on the availability and convenience of these resources, students may choose alternatives over using smartphones.

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   h. **Faculty attitudes.** The willingness of faculty members to incorporate smartphones into the learning process is crucial. Resistance from educators or a lack of training in utilizing smartphones for educational purposes may impede their widespread use.

- Finally, **H11**: *"Higher **USI** Higher **VCB**,"* whose items described as **Q1** and **Q2** (**USI**) express individual preferences for using smartphones as primary tools for achieving learning goals, while **H1** and **H2 (VCB)** highlight concerns about the cost associated with smartphone use. These factors collectively may have a small effect on the widespread use of smartphones in higher education for several reasons:
   a. **Financial considerations.** The high cost associated with smartphones (**H1** and **H2**) can be a significant barrier, especially for students facing financial constraints. The expense of purchasing and maintaining a smartphone, along with related services, may limit its accessibility for some students.
   b. **Institutional support**. The impact of individual preferences (**Q1** and **Q2**) and concerns about costs depends on the level of institutional support. If higher education institutions provide alternatives or support programs to mitigate the financial burden, it may encourage or hinder the widespread adoption of smartphones.
   c. **Equity and inclusion.** The expense associated with smartphone use may contribute to disparities in access among students. This can impact equity and inclusion efforts in higher education, as students with limited financial resources may be at a disadvantage compared to their peers.
   d. **Alternative learning resources.** Higher education institutions typically offer a range of resources, including computer labs, libraries, and online platforms. Students may choose alternative options if they find them more cost-effective, which could limit the overall impact of smartphone use.
   e. **Educational technology policies.** Institutional policies and approaches to educational technology play a crucial role. If universities prioritize affordability and provide support for students to access necessary technologies, it may mitigate the impact of cost concerns.
   f. **Technological infrastructure.** The availability of reliable and affordable internet connectivity, which is essential for effective smartphone use, can vary. If the infrastructure

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is lacking, students may face challenges in fully utilizing smartphones for their learning goals.

g. **Educational pedagogy.** The integration of smartphones into higher education is influenced by the prevailing educational pedagogy. If instructors do not actively incorporate mobile technologies into their teaching methods, the impact of individual preferences and cost considerations may be limited.
h. **Digital literacy.** Students' proficiency in using smartphones for educational purposes also plays a role. The impact may be reduced if there is a lack of digital literacy or understanding of how to leverage smartphones effectively for learning.

6.2. Practical implications

The integration of smartphones in higher education fosters sustainable development by lessening educational gaps among students of varied socioeconomic statuses. Moreover, mobile learning is in harmony with the Sustainable Development Goals (**SDGs**), notably **SDG4**, as it promotes sustainable and high-quality higher education. Furthermore, it enables global education access, fostering an inclusive and fair learning atmosphere**.**

The outlined research methodology offers noteworthy practical contributions with tangible implications for diverse stakeholders. The following are some of the practical contributions based on the **TAM-SHE** framework reinforced with student motivation (**MTV**) and student quality perceptions (**SQY**):

a. **Enhanced understanding of smartphone adoption in higher education**. The research contributes to a deeper comprehension of the factors influencing students' acceptance and adoption of smartphone technology in higher education. By incorporating components such as perceived usefulness, ease of use, attitude, and behavioral intention, the **TAM** model provides a holistic framework to analyze and understand the dynamics of smartphone utilization.
b. **Insights for educational institutions.** The findings can offer valuable insights for educational institutions seeking to integrate and optimize smartphone use in higher education settings. Understanding factors like student self-management (**MNG**), student learning results

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(**LRS**), student achievements perceptions (**SFB**), student cost-benefit considerations (**VCB**), and student expectations (**EXP**) , all of them being the actual system use in **TAM** provides institutions with a nuanced understanding of the diverse aspects influencing technology adoption.

c. **Informed decision-making for policymakers.** Policymakers in the education sector can benefit from the research outcomes to make informed decisions about technology integration and policy development. This can include shaping guidelines, allocating resources, and creating an environment that supports effective smartphone use for educational purposes.

d. **Tailored educational strategies**. Identifying factors such as student motivation (**MTV**) and student quality perceptions (**SQY**) as reinforcements to the **TAM** allows for the development of tailored educational strategies. Institutions can leverage these insights to design interventions that enhance them, fostering a more conducive environment for effective smartphone use in learning.

e. **Guidance for Educators.** Educators can gain practical guidance on how to align their teaching methods with students' technological expectations. For instance, focusing the insights into student expectations (**EXP**), student self-management (**MNG**), and student learning results (**LRS**) can aid educators in designing courses that capitalize on the benefits of smartphone technology.

f. **Student-Centric approach.** The research focuses on understanding students' expectations (**EXP**) promoting a student-centric approach to technology integration. This can lead to creating a more engaging and responsive learning environment that aligns with the preferences and needs of students.

g. **Methodological Contribution.** Applying a literature review to inform the questionnaire design for over **523 Mexican university students** adds a methodological contribution. This approach ensures that the research instruments are culturally relevant and context-specific, enhancing the validity and reliability of the study.

h. **Relevance Post-COVID-19**. The acknowledgment of the impact of the **COVID-19 pandemic** on student motivation (**MTV**) and quality perceptions (**SQY**) underscores the study's relevance in the post-pandemic educational landscape. This recognition allows for a more contemporary understanding of technology acceptance dynamics.

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7. CONCLUSIONS

After the robust qualitative based on Delphi Panel-Focus Group and Analytic Hierarchy Process (**AHP**) and quantitative analysis based on **PLS-SEM**, we highlight the following conclusions as **theoretical contributions:**

a. Multi-faceted **TAM-SHE** Framework: Integrates perceived usefulness, ease of use, attitude, behavioral intention, and actual system use, focusing on smartphone use in higher education.

b. **Comprehensive understanding.** Addresses elements like student self-management (**MNG**), student learning results (**LRS**), student achievement perceptions (**SFB**), student cost-benefit considerations (**VCB**), and student expectations (**EXP**), enhancing understanding of smartphone adoption for higher education (**SHE**) as actual system use to enhance the **TAM.**

c. **Post-COVID-19 analysis.** Recognizes the evolving dynamics of student motivation (**MTV**) and student quality perceptions (**SQY**) in the post-pandemic era, influencing smartphone acceptance.

The **practical contributions** are:

a. Deeper insights for stakeholders. It offers enhanced understanding of smartphone adoption in higher education, informing educational institutions, policymakers, and educators.

b. **Tailored strategies.** It identifies student motivation (**MTV**) and student quality perceptions (**SQY**) as key factors, allowing the development of tailored educational strategies for effective smartphone use.

c. **Methodological contribution.** Applying a literature review to design questionnaires ensures cultural relevance for over **523 Mexican university students**, enhancing the study's validity and reliability of the **TAM-SHE** empirical framework.

d. **Post-COVID-19 relevance.** It acknowledges the impact of the **COVID-19 pandemic** on student motivations (**MTV**) and student quality perceptions (**SQY**), ensuring a contemporary understanding of technology acceptance in education.

Finally, for the **post-COVID pandemic** era, more studies are necessary to verify the new student motivations (**MTV**), student quality perceptions (**SQY**), and the actual system use factors to facilitate mobile technology in use for higher education through the technology acceptance model (**TAM**).

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