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# Adopting xRM in Higher Education: E-Services Outside the Classroom

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**Abstract:** This paper explores the role of extended relationship management (xRM) in the higher education ecosystem. With the ultimate goal of the institution's future sustainable development, the university has developed and implemented a customized model of integrated e-services to foster a relationship with its leading stakeholder group—students. Furthermore, our study introduces a comprehensive model of xRM e-services. The main objective of this paper was to assess students' behavioral intentions, acceptance, and long-term usage of the xRM e-services. A theoretical model was developed based on the UTAUT2 framework. The evaluation of the acceptance and usage of the xRM e-services was assessed by using a partial least squares structural equation modelling (PLS-SEM) methodology. The results indicate that factors such as habit and effort expectancy have a significant relationship with students' behavioral intentions, while there is a strong positive influence of their intentions on actual use of the xRM e-services. The emergence of habit as the strongest predictor of behavioral intention indicates that the digitization of traditional touch-points has become an important part of students' everyday lives at university.

**Keywords:** xRM; stakeholder management; sustainable development; university e-services; UTAUT2



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## 1. Introduction

Many people are aware that information and communications technology (ICT) plays an important role in the higher education context [1–13]. Those who were not, had a chance to convince themselves in 2020.

The time has come; the appearance of an institution's website can have a major impact on prospective students' perception of the institution, and therefore on their decisions. Ruffalo Noel-Levitz [14] found that 69% of student respondents reported that an institution's website affects their perception of a university. In his research Moody [15] concluded that, when it comes to the admission process, a university's use of ICT influences the student college selection process as a primary factor in choosing their college or university. It is clear that as technology develops and advances, and thus becomes more and more present in our lives, it will occupy an important place in education as well. It is no longer just a question of whether ICT is present in the form of learning through mobile devices or a distance learning system, but it is a matter of the technological rating of the institution, which leaves a certain impression in the eyes of their stakeholders.

A lot has been said in the area of adopting ICT in the higher educational ecosystem. There are numerous studies which explore ICT from various perspectives, such as usage of mobile devices in education, e-learning, m-learning, or learning management systems. A vast number of studies were focused strictly on the teaching and learning process. It is clear that the educational process itself is the essence of education. However, higher education institutions (HEI) have to deal with tectonic shifts when it comes to how they interact with their users: students and their parents, teaching and non-teaching staff, donors, and alumni [16]. This became especially important in the era of the COVID-19 pandemic, which forced a new model of university–student relationship upon educational institutions.

It has long been known that building and maintaining strong customer relationships is the key to sustainable success in any business [17–20]. Subsequently, taking fast-paced digital shifts into account, higher education institution's management nowadays should focus on building better relationships with its stakeholders [21,22]. In his work Bejou [23] suggest adopting customer relationship management (CRM) as a way to establish and foster connections between students and the HEI. Customer care is present in specific ways in many educational institutions; there is personnel or even whole departments dedicated to providing student services. However, managing relationships with stakeholders successfully takes much more than an individual or department. The institution should develop a specific service-centered environment, where everyone is striving to contribute in an adequate way [24]. Moreover, this study stands out by developing a theoretical model based on a UTAUT2 framework for the purpose of investigating the antecedents of the actual use of xRM e-services, from the students' perspective.

Numerous studies have explored the CRM concept in higher education settings from various perspectives, such as critical success factors and implementation of CRM [25], CRM and e-learning [26,27], CRM solutions and features [28], CRM and sustainable development [20], the adoption process of CRM [29,30], CRM approach and student satisfaction [31], and the role of CRM in recruiting students [32].

How can proper use of technologies improve the rating of an institution in today's competitive market? Take, for example, the situation that has changed the way the world behaves; the COVID-19 pandemic. If there were not any university IT e-services, the university–student relationship would have been extremely disrupted. Never before has the application of information technologies in the everyday relationship between universities, teachers, and students come to the fore. We are not just talking about the educational process, but about the comprehensive relationship that an educational institution has with its students; the need to digitize as many touch points as possible. This has become very important and will become more and more important in the future. In the uncertain times ahead, institutions need to be prepared for the new technological challenges that may lie ahead. It is necessary to explore what the institution can do in terms of building quality relationships with its stakeholders, in order to maintain and even improve the relationships it has with them. In these circumstances, the proper application of ICT can be invaluable to HEI managers, deans, decision makers, administrators, and others, who make important strategic decisions.

Furthermore, a fact that will be of great importance in the future is the following: as the years go by, new generations of students come with increasing knowledge, prior education, and, most importantly, the expectation of the presence of ICT in their study experience. Prospective students will need to be provided with an easier way to study in the first place (including various types of distance learning systems) but also with the opportunity to complete all their obligations outside of the classroom quickly and easily. They need to be provided with all relevant information at their fingertips.

Very few studies have investigated the factors that affect the adoption of university IT e-services for the purpose of nurturing relationships with students. Technological acceptance is very important to be successful in this fast paced century of technology [33]. Our study is an attempt to fill the research gap by investigating the adoption of modern IT e-services integrated into a comprehensive xRM model, which enable higher education institutions to sustainably maintain and develop relationships with their students. This study stands out by developing a theoretical model based on a UTAUT2 framework for the purpose of investigating the antecedents of the actual use of xRM e-services, from the students' perspective. Hence, there is a need to identify the main factors that influence students' acceptance and use of university services.

With the purpose of identifying the underlying motivating factors behind attitudes to using technology, this study focuses on the following research questions:

- Which factors affect the adoption and use of the xRM e-services?
- To what extent do students perceive university xRM e-services as helpful and useful?
- To what extent do student perceive the university xRM e-services as easy to use?
- Do social factors affect students' use of the available xRM e-services?

## 2. Literature Review and Research Hypotheses

### *2.1. xRM*

The basic idea that Freeman exposed in his book [34] states that organizational systems dedicated to managing customer relationships have a better chance of staying effective and competitive in the market compared to organizations that neglect this idea. Ignoring stakeholder relationships can bring a HEI's performance into question. The HEI should meet stakeholders' information needs and communicate systematically with them. Relationships with stakeholders should meet desirable quality criteria, as a satisfied stakeholder has a higher retention rate than an unsatisfied one.

Present-day students want continuous, relevant, and complete communication with their HEI. They expect to get a service from the HEI that is on the same level as other corporations' services: quick responses to their questions, high availability through multiple communication channels, and being treated as individuals rather than numbers [35]. In such a dynamic and complex business environment, accomplishing all these requirements is close to impossible without taking proper care of customer relationship management. CRM in higher education is mainly related to learning activities [26,27]. However, besides the learning process as such, other touch-points and activities that students have on a daily basis with their HEI also play a significant role in creating and maintaining the customer relationship with them, and which will ultimately influence their satisfaction. Therefore, this suggested integrating modern IT e-services into a comprehensive xRM model.

xRM (anything/extended relationship management) represents an IT environment whose goal is to efficiently manage relationships with a wide range of stakeholders, meeting their needs and providing them with all the necessary information through adequate communication channels. xRM represents extended relationship management; the "x" in its name replaces any entity that relations are being built with, for example, employee relationship management or supplier relationship management [36]. xRM is still a new concept in the literature, and so far has not found a place in higher educational settings. Simply put, xRM extends the approach and strategy of the CRM concept. xRM enables the organizational system to manage a wide range of relations that exist in their business environment: suppliers, employees, assets, and clients; almost anyone that has a certain level importance to their business.

From the "student as a customer" perspective [37], educational xRM should enable digitization of all traditional student touch-points, such as everyday administration processes, admission, enrollment, relevant information sharing, e-learning, Q&A, and similar, through one endpoint system, which would be capable of fulfilling all needs that every individual student has [38,39].

### *2.2. Higher Education Institutions' xRM Model*

One of our goals was to develop a xRM framework that consists of contemporary IT services and that helps the HEI bring their relationship with their students to the next level. This model includes e-business technologies, such as electronic individual student process records [40], mobile instant messaging, social media, distance learning systems, educational integrated informational systems, and other forms of digital relationship management between the HEI and its stakeholders. A comprehensive xRM framework for an educational institution in the complex business ecosystem of higher education is shown in Figure 1.

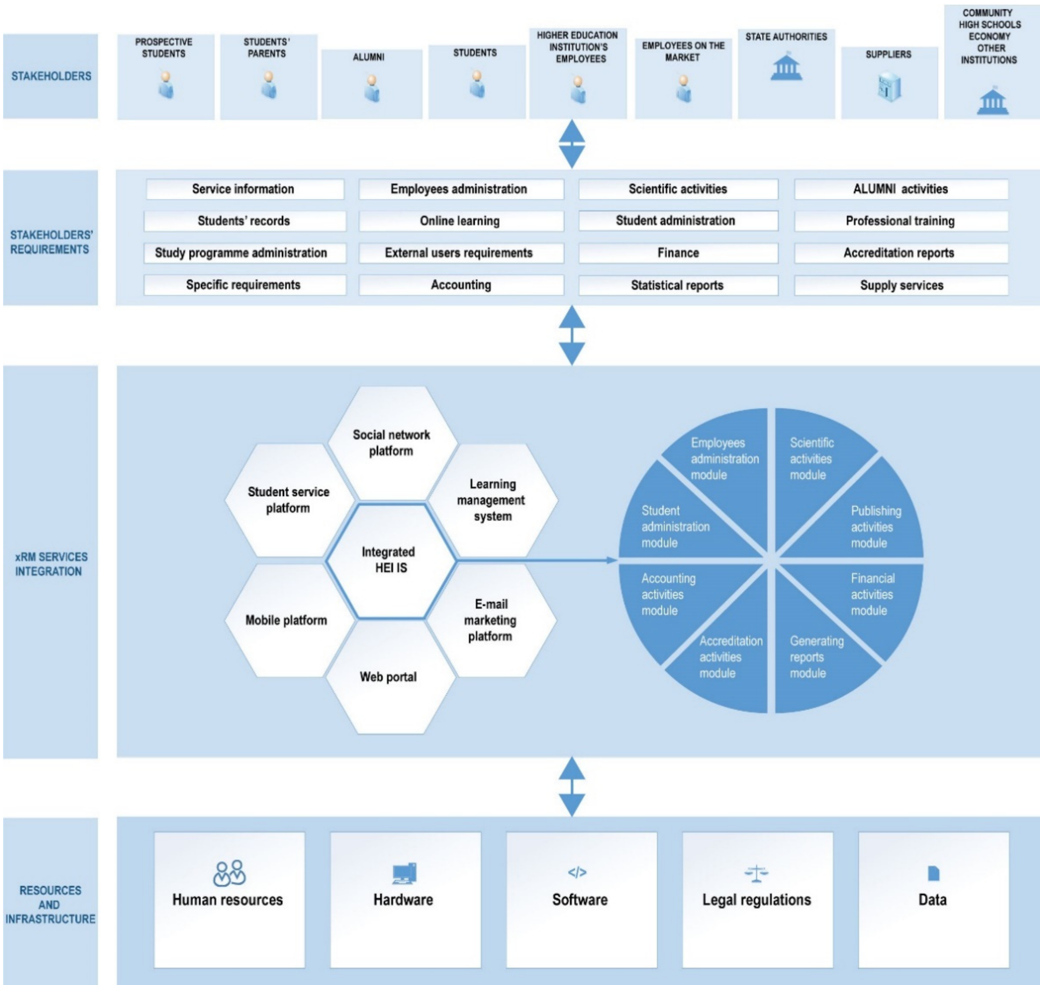


**Figure 1.** xRM model of a higher educational institution.

The model takes care of the relationship management with all the stakeholders of the higher education institution, among which students are the most demanding group in terms of the number of IT services they need to have provided. In addition to relations with stakeholders, the model represents the required infrastructure/support for the proper and efficient business functions: marketing, education, science, human resource management, finance, accounting, and procurement.

Benefits of implementing a xRM system in higher education could include:

- fostering communication;
- better enrollment management;
- marketing and event management;
- simplified, electronic application process (no printed documents)
- monitoring financial flow;
- reporting and analytics;
- integration with other platforms such as a student web portal, social media, and information systems.

### *2.3. UTAUT2*

Venkatesh et al. [41] designed the unified theory of acceptance and use of technology (UTAUT) as a technology acceptance model. By reviewing and synthesizing eight prominent models of technology use, a unified theory of acceptance and use of technology was established. UTAUT model was formulated with four core determinants of intention and usage that play a significant role as direct determinants of user acceptance and usage behavior: Performance expectancy, effort expectancy, social influence, and facilitating conditions.

Performance expectancy is defined as the level to which an individual believes that using the specific IT system will help him or her to attain gains in job performance. Effort expectancy is the degree of ease associated with the use of such a system. Social influence is defined as the level to which an individual perceives that significant others (family, professors, friends, colleagues) believe he or she should use the system. Lastly, Facilitating conditions are the measure of organizational and technical infrastructure support availability for the use of the system [41].

Since its original publication, UTAUT has served as a baseline model and has been widely employed in technology adoption and diffusion research in both organizational and non-organizational settings [42]. UTAUT's unified overview indicated this model as one of the most used and most reliable models in the technology acceptance context. According to Ameri et al. [6], "the newly suggested UTAUT model is known to have 20% to 30% greater explanatory power than the TAM (technology acceptance model)".

Paying particular attention to consumer use context, Venkatesh et al. extended the baseline model by adding new constructs (hedonic motivation, price value, habit) and excluding voluntariness of use [43]. In such a way, UTAUT2 was introduced, which is the theoretical framework for this study. We decided to exclude hedonic motivation and price value, as these constructs are mostly intended for a consumer context and not an organizational context (which an educational institution is a part of). Moreover, the price value construct is not applicable for free of charge technologies, which are the part of the xRM model that this study investigates. That brought us to the conceptual research model adapted to educational environment needs, shown in Figure 2.

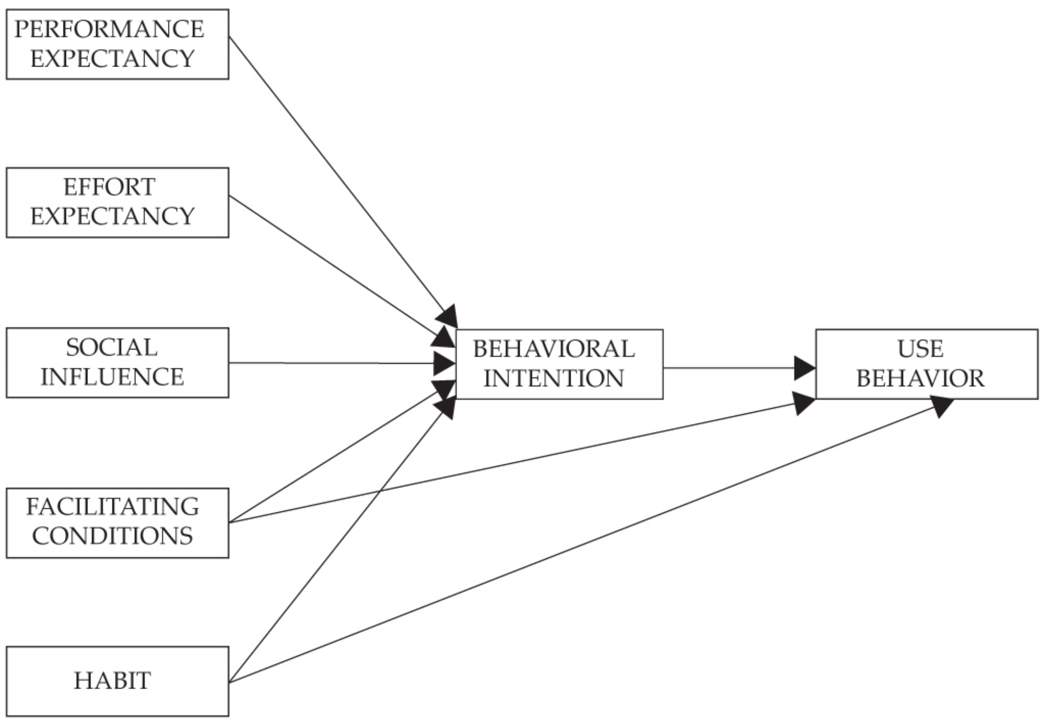


**Figure 2.** Research model.

Our research model consists of seven constructs: Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC), Habit (HT), Behavioral intention (BI), and Use behavior (USE).

Performance expectancy is defined as the level to which an individual believes that using the specific IT system will help him or her to attain gains in job performance.

Venkatesh et al. [41] defines this as the "extent to which using a technology will offer benefits to a customer in performing certain activities". In previous literature, the performance expectancy was detected as one of the factors that has an important influence on user's intention to use technology. According to Dajani et al., students find it to apply IT in the learning process, as it allows them to accomplish tasks more efficiently [8]. This is in line with the work of several other researchers, such as Ameri et al. [6], Nikolopoulou et al. [5], Stebner et al. [44], and Tosuntas et al. [45]. In the context of this research, performance expectancy represents a students' perceived benefits of using the xRM e-service as a tool that enables them to finish their university-related tasks more quickly and efficiently. Thus, the following was hypothesized:

**Hypothesis 1 (H1).** *PE has a positive impact on students' BI to use xRM e-services.*

Effort expectancy is the degree of ease associated with the use of such a system [41]. It is suggested as a direct predictor of attitudes toward use [4]. According to Samsudeen and Mohamed [7], effort expectancy was the most influential determinant of behavioral intention to use e-learning system. Other studies conducted by Dajani et al. [8], Mtebe and Raisamo [46], and Moghavvemi et al. [12] acknowledged that effort expectancy has a direct impact on users' attitudes towards use.

This research puts effort expectancy in the context of students' engaging less exertion to achieve their everyday tasks such as getting necessary information, accomplishing administrative tasks, acquiring knowledge using LMS, communication with the University departments, and similar. The main assumption that lies behind this construct is that students will be more likely adopt new technology that requires little effort to use. To understand the concept, the following hypothesis is proposed:

**Hypothesis 2 (H2).** *EE has a positive impact on students' BI to use xRM e-services.*

In the context of IT products or services, social influence is defined as the level to which an individual perceives that significant others believe he or she should use a particular technology. According to Venkatesh et al. [41] "social influence is represented as subjective norms, social factors, and image". In the present study social influence relates to how students perceive the opinion of their important colleagues, professors, family, and friends about the usage of IT services during their study life. Venkatesh et al. [41] argue that social influence can have an impact on behavioral intention in an environment where use of technology is mandatory, opposed to a voluntary environment. In our case, a small portion of xRM e-services are mandatory for students, and they are related to administrative tasks.

The effect of the social influence can be stronger among younger students [12]. It has been shown that undergraduate students are concerned about their colleagues opinion [7] when it comes to technology acceptance. Moreover, the study that was conducted by Ain et al. [47] showed that social influence had an significant effect on behavioral intention to adopt the learning management system.

Based on these contributions, the following was hypothesized:

**Hypothesis 3 (H3).** *SI has a positive impact on students' BI to use xRM e-services.*

Facilitating conditions are the measures of organizational and technical infrastructure support availability for the use of the system. This factor is related to the possession of sufficient resources and support for individuals to use the technology [41].

In the context of this study, facilitating conditions represent knowledge, instructions, and manuals on one side, and the IT infrastructure and resources on the other side. In addition, the presence of the university's (teachers and IT staff) direct support is a factor that can have a strong impact on students' behavioral intention to use services. All of this is necessary to enable students to easily use university IT services. Missing any of these elements can suppress the students' acceptance of technology [48]. Students will have a positive attitude towards technology acceptance if sufficient resource are available [8].

In accordance with the previous points, the following were hypothesized:

**Hypothesis 4 (H4).** *FC has a positive impact on students' BI to use xRM e-services.*

**Hypothesis 5 (H5).** *FC has a positive impact on the students' actual USE of xRM e-services.*

In the context of using technology, habit is defined as an individuals' repetitive or automatic behavior. Venkatesh et al. [42] defines it as "a perceptual construct that reflects the results of prior experiences". Insights provided by Moorthy et al. [9] show that the most influential construct towards behavioral intention was habit. This is congruent with the findings of another study by Qureshi et al. [10], where habit was also the strongest determinant. Tarhini et al. [49] suggested that students who are used to technology and systems may have positive intentions for further mobile learning usage. Stronger habit leads to a stored intention that in turn influences behavior [42].

Related to this study, we believe that repeated use of university services over an extended period of time can build positive intentions towards them, as the university xRM e-services are used on a daily basis. Habit is expected to show an impact on both the intention to use and the actual use of the university services. Based on these contributions on the role of habit, the following hypotheses are suggested:

**Hypothesis 6 (H6).** *HT has a positive impact on students' BI to use xRM e-services.*

**Hypothesis 7 (H7).** *HT has a positive impact on students' actual USE of xRM e-services.*

Behavioral intention is one of the key predictors of technology use. Davis et al. [50] define behavioral intention as a measure of the strength of an individuals' intention to accomplish a certain behavior. A stronger intention leads to a higher probability that the individual will perform a certain behavior [41,51]. As we have noted before, behavioral intention is influenced by other factors: performance expectancy, effort expectancy, social influence, facility conditions, and habit. Previous studies have shown that behavioral intention has a positive impact on the actual use of technology [1,7,12,49]. In the context of this study, behavioral intention captures students' intention to use the university xRM e-services, so that they can accomplish their activities. It is expected that behavioral intention will have a direct impact on predicting the usage behavior of students to accept and use the university xRM e-services in the following period. Therefore, the following was hypothesized:

**Hypothesis 8 (H8).** *BI has a positive impact on students' actual USE of xRM e-services.*

Many researchers have used the UTAUT model to conduct studies that explore a variety of subjects in a wide range of different environments [52]. Regarding the higher education context, previous studies have mostly used UTAUT/UTAUT2 to explore the acceptance and usage of mobile technologies, regarding learning and the applying of mobile devices in a learning environment [5,6,22,53–63]. No study to date has either explored or evaluated the acceptance and usage by students of academic xRM e-services that serve them outside the classroom.

## 3. Materials and Methods

### *3.1. Sample Size*

The research population was the students of the University Business Academy in Novi Sad, Faculty of Stomatology in Pancevo. The institution is located in Serbia. The survey was conducted in the period between August and November 2020 on a random sample. The sample size was 200 active students, all of whom were asked to fulfill the questionnaire via Google Forms. The majority of the students fulfilled the survey (173, or 82%). The credit for the high response rate could be attributed to the xRM framework itself, as it enabled creating personalized e-mail messages for each student. This may have had a positive impact on their decision to become a part of the research [64].

The demographic characteristics of the data sample are shown in Table 1. Given that the university's overall population consists of 60% female students, it does not come as a surprise that most of the respondents were female (67%). The majority of students were between 20 and 23 years old (69%). As the new academic year had just started when we launched the survey, first-year students were not requested to answer the questionnaire. Their answers would not be relevant, bearing in mind that they were not experienced in using the university xRM e-services.

**Table 1.** Descriptive statistics.

| Demographic Variables | Frequency |
|---|---|
| Age | |
| 19 or younger | 10 (6%) |
| 20 or 21 | 50 (29%) |
| 22 or 23 | 70 (40%) |
| 24 or older | 43 (25%) |
| Gender | |
| Male | 58 (33%) |
| Female | 115 (67%) |
| Study year | |
| Second | 32 (19%) |
| Third | 51 (29%) |
| Fourth | 52 (30%) |
| Fifth | 38 (22%) |

Univariate extremes were identified via a box plot for each variable and are shown in Figure 3. Cook's distance indicator [65] was used to identify multivariate extremes. Eight multivariate extreme values were identified, which were excluded from further analysis. In addition to these, four more respondents who did not give complete answers were excluded from the analysis, so that the final sample on which the confirmatory analysis was performed contained 161 respondents. There was no missing data among them.

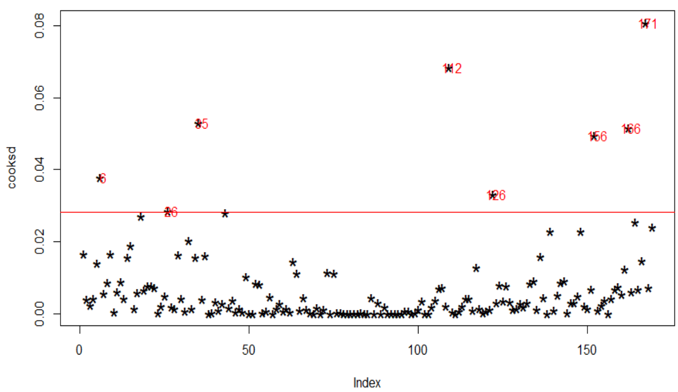


**Figure 3.** Multivariate extreme values.

## 3.2. Questionnaire Design

The questionnaire was divided into two parts: the first was related to demographic information (age, gender, and year of study) and the second part was related to the UTAUT2 model, where 26 questions were divided into seven constructs:

- Performance Expectancy (PE)

- Effort Expectancy (EE)
- Social Influence (SI)
- Facilitating Conditions (FC)
- Behavioral Intentions (BI)
- Habit (HB)
- Use Behavior (USE)

The UTAUT2 questionnaire was translated from English to Serbian. Some of the questions were adapted so they suited the needs of the educational context in this research. A five-point Likert range (1 = very low to 5 = very high) was used to answer the 26 questions. Each construct of questionnaire items is shown in Table 2.

**Table 2.** Questionnaire items.

| Code | Items | Source |
|---|---|---|
| | PERFORMANCE EXPECTANCY items | |
| PE1 | I find university IT e-services useful in my study process | [41] |
| PE2 | Using the university IT e-services makes communication with university quicker | [41] |
| PE3 | Using the university IT e-services saves my time | [6] |
| PE4 | Using the university IT e-services makes my student life easier | [6] |
| PE5 | By using the university IT e-services I get all of the important information on time | [5] |
| PE6 | University IT e-services fulfill my needs regarding student administration | Self-developed |
| | EFFORT EXPECTANCY items | |
| EE1 | I find the university IT e-services easy to use | [41] |
| EE2 | Interaction with the university IT e-services does not require a lot of mental effort | [66] |
| EE3 | Learning how to use the university IT e-services is easy for me | [41] |
| | SOCIAL INFLUENCE items | |
| SI1 | People who are important to me think that I should use the university IT e-services | [41] |
| SI2 | My colleagues (professors and students) think that using IT e-services is important | Self-developed |
| SI3 | The university has been supportive in the use of the university IT e-services | [41] |
| | FACILITATING CONDITIONS items | |
| FC1 | I have the knowledge necessary to use the university IT e-services | [41] |
| FC2 | I have the resources necessary to use the university IT e-services | [41] |
| FC3 | I can get help from others when I have difficulties using the university IT e-services | [41] |
| | BEHAVIORAL INTENTIONS items | |
| BI1 | I intend to use the university IT e-services in the next semester | [41] |
| BI2 | I would suggest other colleagues to use university IT e-services | Self-developed |
| BI3 | I plan to use the university IT e-services for handling my student tasks in the next semester | [67] |
| BI4 | I think it is a wise idea to use the university IT e-services | [68] |
| | HABIT items | |
| HB1 | The use of university IT e-services has become a habit for me | [42] |
| HB2 | Usage of university IT e-services has become natural for me | [42] |
| HB3 | I am motivated to use university IT e-services in the next period | Self-developed |
| | USE BEHAVIOR items | |
| USE1 | I regularly use university IT e-services during my studies | [5] |
| USE2 | Using university IT e-services is a pleasant experience for me | [5] |
| USE3 | I use university IT e-services as a regular part of my study process | [5] |
| USE4 | I use many of the university IT e-services (E-student, University Instant messaging community, University web site, University social media networks, Moodle platform, University e-mail service etc.) | [47] |

In general, respondents answered most of the questions with high grades (Table 3, descriptive statistics and normality tests, column mean), which shows that the vast majority of students generally accept the usage of xRM e-services and have a positive opinion of them.

**Table 3.** Descriptive statistics and normality tests.

| Item | Construct | Kolmogorov–Smirnov | | Shapiro–Wilk | | Kurtosis | Skewness | Mean | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|
| | | **Stat.** | ***p*** | **Stat.** | ***p*** | | | | |
| PE1 | Performance Expectancy | 0.959 | 0.000 | 0.701 | 0.000 | 4.318 | −1.476 | 4.317 | 1.021 |
| PE2 | | 0.959 | 0.000 | 0.709 | 0.000 | 4.526 | −1.444 | 4.342 | 0.962 |
| PE3 | | 0.959 | 0.000 | 0.621 | 0.000 | 6.558 | −1.986 | 4.484 | 0.916 |
| PE4 | | 0.946 | 0.000 | 0.697 | 0.000 | 5.166 | −1.621 | 4.329 | 1.005 |
| PE5 | | 0.946 | 0.000 | 0.801 | 0.000 | 3.063 | −0.990 | 4.037 | 1.117 |
| PE6 | | 0.952 | 0.000 | 0.806 | 0.000 | 3.093 | −0.951 | 4.062 | 1.071 |
| EE1 | Effort Expectancy | 0.965 | 0.000 | 0.618 | 0.000 | 5.759 | −1.857 | 4.491 | 0.916 |
| EE2 | | 0.955 | 0.000 | 0.559 | 0.000 | 7.850 | −2.271 | 4.553 | 0.908 |
| EE3 | | 0.959 | 0.000 | 0.570 | 0.000 | 7.257 | −2.171 | 4.547 | 0.901 |
| SI1 | Social Influence | 0.940 | 0.000 | 0.727 | 0.000 | 4.853 | −1.515 | 4.255 | 1.032 |
| SI2 | | 0.949 | 0.000 | 0.774 | 0.000 | 4.233 | −1.225 | 4.174 | 0.997 |
| SI3 | | 0.946 | 0.000 | 0.752 | 0.000 | 3.812 | −1.286 | 4.174 | 1.087 |
| FC1 | Facilitating Conditions | 0.968 | 0.000 | 0.531 | 0.000 | 10.463 | −2.647 | 4.609 | 0.830 |
| FC2 | | 0.961 | 0.000 | 0.510 | 0.000 | 10.190 | −2.670 | 4.621 | 0.851 |
| FC3 | | 0.959 | 0.000 | 0.656 | 0.000 | 6.347 | −1.860 | 4.453 | 0.894 |
| BI1 | Behavioral Intentions | 0.961 | 0.000 | 0.528 | 0.000 | 8.407 | −2.384 | 4.602 | 0.861 |
| BI2 | | 0.955 | 0.000 | 0.611 | 0.000 | 6.517 | −1.972 | 4.484 | 0.936 |
| BI3 | | 0.961 | 0.000 | 0.580 | 0.000 | 7.274 | −2.129 | 4.547 | 0.880 |
| BI4 | | 0.934 | 0.000 | 0.570 | 0.000 | 6.081 | −2.027 | 4.453 | 1.078 |
| HB1 | Habit | 0.934 | 0.000 | 0.649 | 0.000 | 5.867 | −1.085 | 4.373 | 1.042 |
| HB2 | | 0.909 | 0.000 | 0.689 | 0.000 | 4.557 | −1.583 | 4.217 | 1.176 |
| HB3 | | 0.938 | 0.000 | 0.675 | 0.000 | 4.783 | −1.683 | 4.298 | 1.106 |
| USE1 | Use Behavior | 0.943 | 0.000 | 0.623 | 0.000 | 6.129 | −1.918 | 4.429 | 1.011 |
| USE2 | | 0.946 | 0.000 | 0.752 | 0.000 | 3.814 | −1.273 | 4.186 | 1.079 |
| USE3 | | 0.959 | 0.000 | 0.683 | 0.000 | 4.397 | −1.523 | 4.342 | 1.025 |
| USE4 | | 0.977 | 0.000 | 0.606 | 0.000 | 5.587 | −1.826 | 4.578 | 0.764 |

## 4. Results

This study applied the PLS-SEM statistical method for testing the hypotheses. As one of its main advantages, PLS-SEM excels in its high degree of statistical power, which enables it to be more likely to detect relationships as significant when they really exist. Moreover, it can also handle small and large sample size data [69].

Furthermore, PLS-SEM is the preferred method when working with a non-normal data set, as it shows higher robustness in this case [70]. In Table 3, we show the results of the normality test that was performed for each indicator using the Kolmogorov–Smirnov and Shapiro–Wilk tests [71]. As seen from Table 3, a high level of Kurtosis and Skewness coefficients not being near zero indicates that the data distribution is non-normal. Owing to its flexibility and approach of not making distributional assumptions, the PLS-SEM method is adequate for analyzing exactly this type of data sample [70].

Partial least square path analysis was performed using the SmartPLS software tool [72]. As the first step, we tested the measurement model.

### *4.1. Measurement Model*

There are four steps in assessing the reflective measurement model [70]:

1. Examining the indicator loadings,
2. Internal consistency reliability, by Cronbach's alpha and/or composite reliability,
3. Convergent validity,
4. Discriminant validity.

To estimate the relationship between the reflective variables and their indicators, we also assessed outer (indicator) loadings. As seen from Table 4, all outer loadings are above the standard benchmark value of 0.7, which shows sufficient levels of indicator reliability [70]. Moreover, as the loadings (in bold) consistently exceeded the cross-loadings, we can conclude that discriminant validity was established as well. In addition, each item's factor loading, regarding its construct, was statistically significant.

**Table 4.** Indicator's outer loadings and cross-loadings.

| Items | PE | EE | SI | FC | HT | BI | USE |
|---|---|---|---|---|---|---|---|
| PE1 | **0.814** | 0.666 | 0.677 | 0.654 | 0.689 | 0.658 | 0.704 |
| PE2 | **0.843** | 0.630 | 0.680 | 0.617 | 0.618 | 0.598 | 0.665 |
| PE3 | **0.870** | 0.615 | 0.668 | 0.603 | 0.706 | 0.687 | 0.695 |
| PE4 | **0.880** | 0.609 | 0.660 | 0.625 | 0.744 | 0.699 | 0.762 |
| PE5 | **0.786** | 0.584 | 0.685 | 0.475 | 0.566 | 0.587 | 0.61 |
| PE6 | **0.807** | 0.663 | 0.700 | 0.610 | 0.615 | 0.564 | 0.664 |
| EE1 | 0.707 | **0.915** | 0.686 | 0.775 | 0.632 | 0.660 | 0.719 |
| EE2 | 0.611 | **0.847** | 0.606 | 0.633 | 0.598 | 0.629 | 0.681 |
| EE3 | 0.697 | **0.921** | 0.698 | 0.825 | 0.669 | 0.657 | 0.711 |
| SI1 | 0.793 | 0.747 | **0.831** | 0.712 | 0.721 | 0.662 | 0.733 |
| SI2 | 0.574 | 0.536 | **0.856** | 0.531 | 0.599 | 0.560 | 0.603 |
| SI3 | 0.671 | 0.576 | **0.853** | 0.529 | 0.574 | 0.554 | 0.621 |
| FC1 | 0.622 | 0.692 | 0.579 | **0.884** | 0.653 | 0.599 | 0.622 |
| FC2 | 0.622 | 0.750 | 0.633 | **0.920** | 0.641 | 0.651 | 0.626 |
| FC3 | 0.655 | 0.762 | 0.657 | **0.844** | 0.679 | 0.566 | 0.702 |
| BI1 | 0.704 | 0.615 | 0.582 | 0.577 | 0.707 | **0.931** | 0.73 |
| BI2 | 0.739 | 0.765 | 0.696 | 0.690 | 0.783 | **0.943** | 0.801 |
| BI3 | 0.600 | 0.508 | 0.549 | 0.469 | 0.718 | **0.887** | 0.719 |
| BI4 | 0.723 | 0.737 | 0.728 | 0.743 | 0.883 | **0.896** | 0.837 |
| HB1 | 0.754 | 0.671 | 0.693 | 0.731 | **0.953** | 0.815 | 0.833 |
| HB2 | 0.763 | 0.659 | 0.716 | 0.717 | **0.946** | 0.746 | 0.835 |
| HB3 | 0.729 | 0.677 | 0.727 | 0.668 | **0.938** | 0.847 | 0.855 |
| USE1 | 0.724 | 0.680 | 0.683 | 0.685 | 0.817 | 0.766 | **0.907** |
| USE2 | 0.781 | 0.708 | 0.752 | 0.697 | 0.857 | 0.764 | **0.902** |
| USE3 | 0.753 | 0.758 | 0.720 | 0.636 | 0.806 | 0.805 | **0.915** |
| USE4 | 0.563 | 0.562 | 0.502 | 0.516 | 0.561 | 0.576 | **0.72** |

Notes. Values in bold represent factor loadings.

The internal consistency reliability of the reflective measurement model was examined through Cronbach's alpha, which estimates the reliability based on the intercorrelations of the observed indicator variables [70]. Coefficients resulting above 0.7 for each item show high internal consistency and reliability. Besides Cronbach's alpha, composite reliability (which varies between 0 and 1) was used to determine the internal consistency reliability. Higher values of composite reliability indicate more robust levels of reliability. In our case, the composite reliability ranged from 0.884 to 0.962. In order to confirm internal reliability, composite reliability values should be greater than 0.7 [6,70]. As Hair et al. state [70] "Cronbach's alpha is a conservative measure of reliability (i.e., it results in relatively low-reliability values). In contrast, composite reliability tends to overestimate the internal consistency reliability, thereby resulting in comparatively higher reliability estimates. Therefore, it is reasonable to consider and report both criteria".

Convergent validity represents the degree to which a measure positively correlates with alternative measures of the same construct [70]. To evaluate the convergent validity of the reflective constructs, we considered the outer loadings of the indicators and the average variance extracted (AVE). The convergent validity of latent variables was assessed by average variance extracted/explained (AVE), and this ranged from 0.72 to 0.90, which is above the recommended threshold minimum of 0.5, so it can be stated that convergent validity was established.

Table 5 shows the results for Cronbach's alpha, composite reliability, and average variance extracted.

**Table 5.** Internal consistency reliability and convergent validity indexes of the measurement model.

| Constructs | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| Performance expectancy | 0.912 | 0.932 | 0.695 |
| Effort expectancy | 0.875 | 0.924 | 0.801 |
| Social influence | 0.804 | 0.884 | 0.717 |
| Facilitating conditions | 0.858 | 0.914 | 0.780 |
| Habit | 0.941 | 0.962 | 0.895 |
| Behavioral intentions | 0.935 | 0.954 | 0.837 |
| Use behavior | 0.885 | 0.922 | 0.748 |

The last step was to assess discriminant validity, representing the extent of construct uniqueness compared to other constructs in a model. We examined three measures of discriminant validity: the cross-loadings (already shown in Table 4), the Fornell–Larcker criterion (Table 6), and the heterotrait–monotrait ratio (HTMT, Table 7). The Fornell–Larcker criterion compares the square root of the average variance explained (AVE) with the latent variable correlations. Each construct's AVE square root (in bold) should be greater than its highest correlation with any other construct [70], which was achieved.

**Table 6.** Fornell–Larcker criterion matrix.

| Constructs | PE | EE | SI | FC | HB | BI | USE |
|---|---|---|---|---|---|---|---|
| PE | **0.834** | | | | | | |
| EE | 0.751 | **0.895** | | | | | |
| SI | 0.811 | 0.742 | **0.847** | | | | |
| FC | 0.717 | 0.833 | 0.707 | **0.883** | | | |
| HB | 0.791 | 0.708 | 0.753 | 0.745 | **0.946** | | |
| BI | 0.762 | 0.725 | 0.704 | 0.686 | 0.850 | **0.915** | |
| USE | 0.822 | 0.786 | 0.777 | 0.737 | 0.860 | 0.848 | **0.865** |

Notes. Values in bold represent square root of the average variance extracted.

**Table 7.** Heterotrait–monotrait ratio of correlations (HTMT).

| Constructs | PE | EE | SI | FC | HB | BI | USE |
|---|---|---|---|---|---|---|---|
| **PE** | | | | | | | |
| **EE** | 0.843 | | | | | | |
| **SI** | 0.840 | 0.872 | | | | | |
| **FC** | 0.810 | 0.760 | 0.838 | | | | |
| **HB** | 0.850 | 0.779 | 0.856 | 0.830 | | | |
| **BI** | 0.818 | 0.793 | 0.798 | 0.756 | 0.839 | | |
| **USE** | 0.809 | 0.862 | 0.805 | 0.842 | 0.865 | 0.822 | |

As a last method for examining the discriminant validity, we used the heterotrait–monotrait (HTMT) criterion. This ratio measures the similarity between constructs. According to Henseler et al. [73], HTMT values lower than 0.9 show that discriminant validity is established. As seen from Table 7, all of the values are below the suggested threshold of 0.9, confirming the model's discriminant validity.

In order to detect common method variance (CMV) in our model, we used the full collinearity test proposed by Kock and Lynn [74]. This method is based on examining variance inflation factors (VIF) that are generated for every latent variable. The occurrence of a VIF factor greater than 3.3 represents the existence of collinearity among the variables. When a full collinearity test shows that all VIFs are lower than 3.3, the model can be considered free of common method bias [75]. The full collinearity estimates are shown in

Table 8 and reveal that our model does not have any multicollinearity issues, as the values of VIF are less than 3.3.

**Table 8.** Variance Inflation Factor (VIF).

| Outer VIF | | Inner VIF | |
|---|---|---|---|
| **Item** | **Value** | **Construct** | **Value** |
| PE1 | 2.268 | Performance Expectancy | 2.136 |
| PE2 | 2.559 | | |
| PE3 | 2.043 | | |
| PE4 | 2.202 | | |
| PE5 | 2.104 | | |
| PE6 | 2.292 | | |
| EE1 | 2.148 | Effort Expectancy | 2.057 |
| EE2 | 1.840 | | |
| EE3 | 2.271 | | |
| SI1 | 1.494 | Social Influence | 1.915 |
| SI2 | 2.005 | | |
| SI3 | 1.997 | | |
| FC1 | 2.567 | Facilitating Conditions | 1.906 |
| FC2 | 2.032 | | |
| FC3 | 1.783 | | |
| BI1 | 2.534 | Behavioral Intentions | 2.391 |
| BI2 | 2.511 | | |
| BI3 | 2.692 | | |
| BI4 | 2.469 | | |
| HB1 | 2.059 | Habit | 2.491 |
| HB2 | 2.675 | | |
| HB3 | 2.763 | | |
| USE1 | 2.134 | Use Behavior | - |
| USE2 | 2.125 | | |
| USE3 | 2.369 | | |
| USE4 | 1.539 | | |

As for the model fit in a PLS-SEM context, the standardized root mean square residual (SRMR) and goodness-of-fit (GOF) were assessed. The GOF index is an overall measure of model fit for PLS-SEM [70]. This index verifies if a model sufficiently explains the empirical data and is calculated as the geometric mean of the average communality and the average $R^2$. Its value ranges from 0 to 1, and a bigger value represents better global validation of the path model [76,77]. The SRMR was introduced by Henseler et al. [78] as a measure of estimated model fit for PLS-SEM. Lower SRMR values represent a better model fit, and the cutoff value is 0.8 [79].

The GOF, SRMR, and other indices such as a Chi-Square and NFI were also calculated and their values are shown in Table 9. The GOF value of 0.794 and SRMR value of 0.069 reveal the model's good fit.

**Table 9.** Model fit summary.

| Index | Values |
|---|---|
| GOF | $\sqrt{0.782 \times 0.795} = 0.788$ |
| SRMR | 0.069 |
| d_ULS | 1.918 |
| d_G | 1.630 |
| Chi-square | 1429.329 |
| NFI | 0.940 |

Finally, we can conclude that the results obtained in the previous analyses indicate that it is possible to continue with further examinations and testing of the set hypotheses, i.e., the relationship between the constructs.

*4.2. Structural Model*

To test the statistical significance of the path (or β) coefficients of structural model constructs and the amount of variance explained in the endogenous construct by its exogenous construct (R-square), we used a bootstrapping method with 5000 subsamples as a nonparametric procedure. The results of the structural model with moderated variables included are shown in Figure 4 and Table 10.

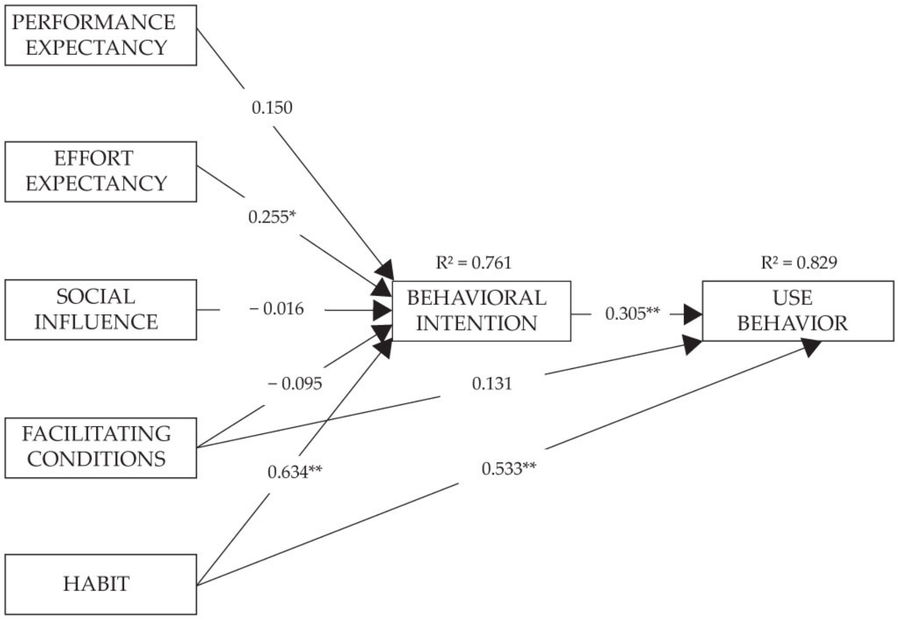


**Figure 4.** Standardized path coefficients and significance of the inner model. Note: numbers represents the standardized path coefficients. ** $p < 0.01$. * $p < 0.05$.

**Table 10.** Structural model results.

| Hypotheses | | Path Coefficients | Confidence Interval 95% | *p* Values | Result |
|---|---|---|---|---|---|
| H1 | PE -> BI | 0.150 | (−0.069, 0.384) | 0.189 | Not supported |
| H2 | EE -> BI | 0.255 | (0.039, 0.470) | 0.020 | Supported |
| H3 | SI -> BI | −0.016 | (−0.181, 0.140) | 0.841 | Not supported |
| H4 | FC -> BI | −0.095 | (−0.360, 0.211) | 0.509 | Not supported |
| H5 | FC -> USE | 0.131 | (−0.024, 0.291) | 0.097 | Not supported |
| H6 | HB -> BI | 0.634 | (0.435, 0.811) | 0.001 | Supported |
| H7 | HB -> USE | 0.533 | (0.348, 0.705) | 0.001 | Supported |
| H8 | BI -> USE | 0.305 | (0.122, 0.514) | 0.002 | Supported |

As seen from Table 10, two hypothesized relationships, between effort expectancy and habit with behavioral intention were supported. Moreover, the hypotheses regarding the relationships between habit and behavioral intention to use xRM e-services were supported.

Effort expectancy (β = 0.249, $p$ = 0.048) and habit (β = 0.642, $p$ = 0.001) positively affected behavioral intention. Furthermore, habit (β = 0.514, $p$ = 0.001) and behavioral intention (β = 0.313, $p$ = 0.002) had a strong bond with use. On the other hand, performance expectancy (β = 0.153), social influence (β = −0.002), and facilitating conditions (β = −0.065) had no significant effect on behavioral intention, or on use.

Regarding the coefficient of determination ($R^2$), the structural model explains 76.1% of the variance of BI and 82.9% of USE. Higher values indicate a greater explanatory power of the model. As a guideline, values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak [69], which indicates that this study's model has a high explanatory power.

## 5. Discussion and Conclusions

### 5.1. Discussion

This study explored the acceptance and usage of the designed and implemented framework of university xRM e-services among students. The COVID-19 pandemic has shown the importance of IT services to all areas of our lives, including the higher education environment. We find the results of this study significant for future education development processes as digital technology has come to play a crucial role in numerous aspects of daily students' lives [80]. To our knowledge, this study was one of the first that explored and evaluated students' acceptance and use of digital technology in an "outside the classroom" context. As such, the results of the study may be useful to HEI leaders, managers, deans, decision-makers, and administrators.

The suggested relationships between constructs were examined, and the results show that four out of the eight hypotheses were supported. This study has found that habit and effort expectancy had a significant effect on students' behavioral intention to use university xRM e-services. Moreover, habit and behavioral intention had a significant influence on the actual use of xRM e-services.

Opposite to the findings of many UTAUT2 based studies [2,5–8,12,63], analysis of the first hypothesis that we proposed showed that there is no significant relationship between performance expectancy and students' behavioral intention. Interestingly, our finding was the same as in a study that had a similar focus (using the UTAUT2 model to analyze students' ICT adoption) conducted by Attuquayefio and Addo [13]. Furthermore, this is aligned with other studies, such as the cases of healthcare environment web-based system adoption [81], mobile learning [9], and learning management system adoption context [10]. Although the mean indicators for the PE construct were relatively high (4.26), our findings show that students do not perceive the use of xRM e-services as a factor that can affect their performance in their study life.

The results show that there is significant relationship between effort expectancy and students' behavioral intention. This is congruent with similar studies [8,11,63], whereas effort expectancy was the most influential determinant of behavioral intention in the context of e-learning [7]. Years of experience have taught us that medical students often show some sort of computer anxiety, especially those who had not previously undergone formal computer courses [82]. Hence, we believe that they pay a lot of attention to the ease of use and expect the interaction with devices and systems to be as easy as possible. The emphasis here is on the ease of use, so service designers should take special care on simplicity when creating and implementing e-services. A suggestion here for HEI managers and administrators would be to simplify the process of using e-services as much as possible, so we suggest the availability of both on-line and off-line support. There is a good chance that students who perceive e-services as easy to use will be more willing to adopt them on a daily basis.

The third hypothesis related to social influence was rejected. According to Venkatesh et al. [41] social influence can have an impact on behavioral intention in an environment where use of technology is mandatory opposed to a voluntary environment. This is in accordance with our case, where just a small portion of xRM e-services are mandatory for students, and they are related to administrative tasks. We believe that students did not consider the community surrounding them to have an impact on their behavior. In addition, we assume that SI does not play an important role, because students can decide for themselves to what extent they will use the services. Teaching staff and the university do not influence students in any way regarding the obligation of using these services. As Tamilmani et al. [52] state, the majority of the studies (around 69%) found this path to be significant, but they reported minimal path values. The remaining 31% of studies reported this path as non-significant, placing this path in the eighth position (compared to other paths) in terms of meta-analysis (β) strength. Thus, we can say that social influence plays a significantly lesser role in influencing individual intentions to use underlying technologies [52].

Although students think that they have sufficient technical and knowledge resources for using these services, the facilitating conditions did not have a significant effect on behavioral intention. All of the xRM e-services are pretty straightforward and have low hardware requirements. Services are available both through desktop and mobile devices. In his study, Hsu [83] reported that FC did not have an important influence on students' behavioral intention towards the acceptance of Moodle. Moreover, there are similar examples from an educational context that are in accordance with this finding [5,6,8,9]. Furthermore, it should be noted that according to Venkatesh et al. [41] if PE and EE constructs are present (as in our case), FC becomes insignificant for predicting intention.

Habit emerges as the strongest predictor of behavioral intention (β = 0.634). This finding shows that digitization of traditional touch-points has become an important part of students' everyday lives at university. This is in accordance with results of Tamilmani's study [52], which conducted a meta-analysis evaluation of 60 UTAUT2 quantitative studies and showed that the path relationships between *Behavioral intention → Use, Habit → Behavioral intention, and Habit → Use* are the top three strongest paths amongst all UTAUT2 relationships. This is also congruent with the latest research that has explored mobile device usage in the learning process [5,6,9].

Positive habit effects on the actual use of xRM e-services is in accordance with previous studies [5,6,54,55]. Students nowadays have a high level of expectation when it comes to the involvement of digital services as a regular part of their studies [84]. The offer and proper use of digital technologies in the portfolio of a higher education institution especially came to the fore during the COVID pandemic. This forced a totally new way of interaction and communication between the student and higher education institution.

Students' behavioral intentions had a direct impact on the actual use of xRM e-services. They expressed a strong willingness for acceptance and long-term use of xRM e-services in the future. These findings are congruent with similar studies [5–7,12,47].

### 5.2. Conclusions

A theoretical model was proposed in order to give a better understanding of the factors that influence students' behavioral intentions to use xRM e-services. By employing the UTAUT2 framework, this study investigated the antecedents of the actual use of xRM e-services, from the students' perspective. The formulated hypotheses were empirically tested by using structural equation modelling (SEM). There were three latent variables that were detected as influential for actual use of services: habit, effort expectancy, and behavioral intention. Together, they explain 83% of the variance in the use of xRM e-services. The results show that there was a significant relationship between the use of xRM e-services and the constructs, in the following order: habit influencing behavioral intention (β = 0.634, $p$ = 0.001), habit influencing use (β = 0.533, $p$ = 0.001), behavioral intention influencing use (β = 0.305, $p$ = 0.002), and effort expectancy influencing behavioral intention (β = 0.255, $p$ = 0.02). Contrary to our expectations, performance expectancy, social influence, and facilitating conditions did not show significant associations with the use of xRM e-services.

A few studies explored technology acceptance from the student perspective based on the UTAUT/UTAUT2 model. However, none of the studies has so far examined students' usage of xRM e-services for "outside the classroom" purposes. In this paper we have responded to the objectives set and have examined the developed hypotheses.

The results of the present study indicate that the most important predictor for students' behavioral intention to use xRM e-services was habit. In addition, habit also had a strong impact on students' actual use of xRM e-services. The research outcomes showed that there was a significant relationship between effort expectancy and behavioral intention towards students' use of xRM e-services.

The practical implications of this research are that students' e-services should be designed and implemented with ease of access in mind, with straightforward instructions which can help students to easily access these services and fulfill their needs. It is therefore believed that students who perceive them as easy to use will be more willing to adopt the xRM e-services. These findings can be useful for HEI policy makers and can help them to maximize the acceptance and the success of new technology initiatives [81]. This could lead to, not only student satisfaction, but also improving the institution's technological reputation.

Today, digital technology has become an essential part of students' everyday lives and has a crucial role in their academic and non-academic activities. We live in a new digital reality [80], and educational institutions will have to adapt to it quickly. The proper use of digital technologies could play an important role in educational institution sustainable development in the future. The upcoming generations of higher education students are increasingly likely to have prominent previous experience with significant use of digital technologies as a part of their elementary and secondary education [85]. As a result, we believe that future events will bring higher education institutions to a crossroad—"digitize or die".

### 5.3. Limitations and Future Research

There were a few limitations in this study that have to be addressed. First, the research was limited to a small sample size. We were not able to overcome this limitation due to the small number of students that study at our university. A future recommendation would be to perform similar research on a bigger sample of university students.

Second, it would be of value to investigate students' attitudes toward acceptance and use of university services in different study areas. Another limitation was that the sample consisted only of students from one study area (dentistry). Future research could fill this gap by comparing students' results from other fields (such as technical, social, natural). We believe that results could differ from field to field, especially compared to technical/computer science.

Similarly, it may prove worthwhile to examine attitudes and readiness of technology acceptance by other the HEI essential stakeholder group—teaching staff. Educational institution's employees use university xRM e-services on an even larger scale, and they do so more often. Future research could incorporate this important stakeholder group, as they have a lot of interaction with the educational institution through certain digital touch-points.

Students' perceptions and behavior patterns at our university may differ from other students who study at other universities in other countries. Thus, it may prove worthwhile to conduct some further evaluations and comparisons, which could include other public and private universities. Moreover, the cultural influence of different developed or developing countries could possibly produce varied results; hence, this could be investigated further.

In addition, it may be valuable to carry out similar research in following periods of time and to compare results, having in mind that the COVID-19 pandemic has significantly impacted the form of the university–student relationship and pattern of behaviors. This study was prepared just before the first pandemic occurred, so it might be relevant to replicate the study over time, with a longitudinal design.

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