Mobile Applications as an Innovation Adoption in Universities: Impact of Age, Size, Previous Technology Transformations and Proximity

Track: Information Technology Management

Abstract:

This paper builds upon previous research on innovation adoption. It aims to discover the effects of proximity, age, size and previous technology transformation patterns on organization innovation adoption. The relations are previewed in the adoption of mobile applications from a sample of 190 universities (3970 observations) around the world. We hypothesize that a higher age, bigger size, more previous technological transformations and higher levels of proximity, support a faster innovation adoption by universities. Results partially support the hypothesis and lead to understand the adoption of innovation in the particular context of innovations influenced by adopting organization´s users.

Keywords: innovation, adoption, mobile applications, proximity

INTRODUCTION

Previous studies have analyzed patterns of technology adoption in consumer contexts and organizational contexts (see Benbasat and Barki 2007; Venkatesh et al. 2003, Venkatesh et al. 2012). Firm size and age and their impact on innovation adoption has been studied by various authors**.** (Cho, 2006; Giunta & Trivieri, 2007; Lee, 2004; Li, Wu, Luo, & Zhang, 2013; Lyytinen & Rose, 2003; Teng, Grover, & Güttler, 2002; Terlaak, King, & Terlaak, 2013)**.** Innovation behavior is also a current area of research, where the effects of previous innovation adoption have been studied. (Li, Wu, Luo, & Zhang, 2013, Barden, 2012) Likewise, "much has been written on the impact of proximity on learning, knowledge creation and innovation (e.g. Amin and Wilkinson, 1999). The purpose of this study is to discover the effects of firm size, age, proximity and previous innovation adoption behavior on the adoption of a new innovation.

This paper seeks to demonstrate that under specific conditions, innovation adoption factors previously empirically tested do not have the same effect on innovation adoption. The conditions refer to innovation adoptions which use are destined directly to its clients and are of support to the core mission of a business. To exemplify and empirically test this situation this research proposes to study the academic sector and the adoption mobile applications.

Organizations may decide to innovate motivated by the desire to incorporate a new technology in search for better efficiency (Fichman, 2004; Jeyeraj, 2006), or to adopt an innovation due to the lack of technical support of their previous technology (e.g., Brown and Venkatesh 2005, Venkatesh et al. 2003). Another reason for adoption might be the image of the organization. An organization will possess a better image when their levels of innovation are higher. Image is defined as "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system." (Moore & Benbasat, 1991). "This image construct reflects external pressure and social expectation variables found in the small business literature." (Lee, 2004) We posit that adoption of mobile applications by universities serve in the most part as support to their students and as a marketing tool intended to show an innovative image, in contrast with being a tool for better efficiency or productivity.

This paper uses the educational sector to test whether the factors denoted as age, size, previous technological transformation and proximity affect the velocity of adoption of mobile applications. We consider the adoption from the perspective of the university as a means to make available the mobile application to its users. We consider this a similar adoption to that of the webpage at the moment of its launch in the education industry. Additionally, we describe the mobile applications as being an innovation.

THEORETICAL FRAMEWORK

The theoretical framework initiates by providing literature on the area of innovation adoption (Abrahamson and Rosenkopf, 1993; Greve, 1996; Roger, 2003; Currarini et al., 2009; Li et al., 2013) and seeks to analyze the effects of organizational age and size on innovation adoption levels (Pan & Jang, 2008; Li, et al., 2013). Literature on previous technological transformations and innovation adoption behavior (Li, et al., 2013) is presented and analyzed for the context of universities and mobile application adoption. Proximity is also considered as a variable which affects innovation adoption. (Howells 2002; Boschma, 2005). We then link the literature to elaborate 4 sets of hypothesis related to each of the literature topics discussed.

DISRUPTIVE INNOVATION

Authors present variations for the definition of disruptive innovation, nonetheless, all possess similarities in that they indicate a change from a previous depart line. "Disruptive innovations are often the outcome of unleashing new product architectures that deviate radically from existing product lines by incorporating novel and unprecedented architectural principles like changing telecommunication service from circuit switching to packet switching, or transforming imaging from an analog to a digital process" (Christensen and Bower 1996; Henderson and Clark 1990; Teece 1986; Utterback 1996) cited in (Lyytinen, 2003).

"Architectural innovations stand out as creative acts of adapting and applying latent technologies or potential to previously unarticulated user needs" (Abernathy and Clark 1985). They radically deviate from an established trajectory of performance improvement, or redefine what performance means in a given industry" (Chistensen and Bower 1996). "They are radical (Zaltman et al. 1977) in that they significantly depart from existing alternatives and are shaped by novel, cognitive frames that need to be deployed to make sense of the innovation" (Bijker 1987). Mobile applications depart from existing alternatives due to the mobility factor and personalization characteristics.

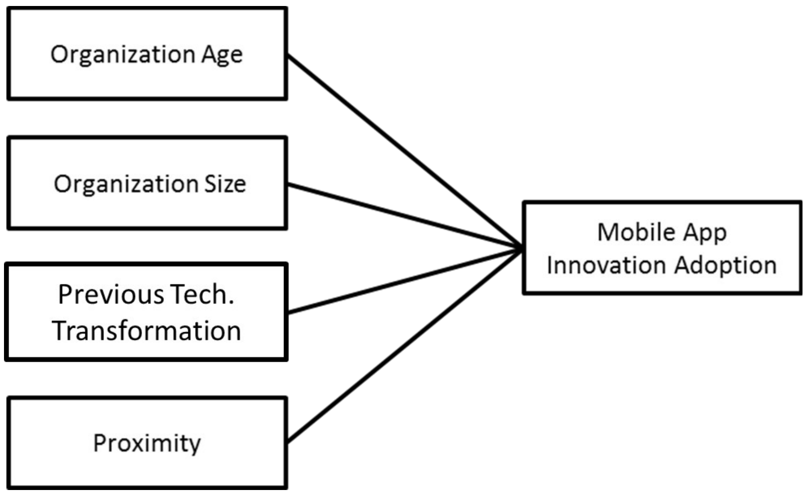
Consequently, disruptive innovations are truly transformative (Abernathy and Clark 1985). To become widely adopted, disruptive architectural innovations demand provisioning of complementary assets in the form of additional innovations that make the original innovation useful over its diffusion trajectory (Abernathy and Clark 1985). To the extent of the previous definitions, mobile applications could be considered disruptive innovations and further interpretation of their use in the educational sector can be construed as well as a disruptive innovation. This supports the existent difference between what will be defined as the previous traditional web page technology (which in turn we consider was a disruptive innovation at the beginning of its time) and the current disruptive mobile application innovation.

Information Transfer

Directly linked with the concept of proximity, information transfer is related to how information reaches actors and affects the innovation adoption of decision makers. "When decision makers lack information about a new technology, they must rely on information sources outside of firm boundaries" (Rogers, 2003). "Observations of others´ adoption behaviors constitute a primary source of that information". Consequently, firms tend to mimic the innovation adoption behaviors of other firms" (Abrahamson and Rosenkopf, 1993; Greve, 1996)

Li et al., (2013) reached conclusions regarding how homophily affects innovation adoption in social networks. Homophily is defined as "the tendency of people to associate with others similar to themselves" (Currarini, et. al, 2009).

The results of Li et al. are of major relevance to the present study due to the transfer of information available between competing and non-competing universities and the relation to proximity. Li et al., (2013) concludes that "if we want to boost the innovation adoption, we should try to decrease the adoption cost, or enrich the links among these agents, especially enhance the homophily obtained from endogenous variables of this system, or encourage the agents to make them brave and not to care the others' decisions too much". In the case of mobile applications, arguably the cost of the innovation is not high or one that would prohibit the innovation adoption or limit the financial strength of the universities. This would leave most of the attention on the expected benefits of adoption. Since the adoption of mobile applications by universities is destined to serve university students, the expected value of adopting the mobile application is clearly affected by the value students give to mobile apps. Therefore, analyzing the success of other universities´ mobile app adoption will provide valuable input to new adopters.



ADOPTION AND ORGANIZATION AGE

New organizations are flexible and structurally simpler than larger organizations (Li, Wu, Luo, & Zhang, 2013). This would lead to think that newer organizations are more prone to adopt new technologies and innovations. As seen in Gambardella and Torrisi (2001), "the younger firms might well prove more ready to embrace innovative developments and carry out the company reorganization that goes along with IT investment" Cited in (Giunta & Trivieri, 2007). As proposed by Giunta & Trivieri, (2007) a negative relation would exist between age and IT adoption.

Nevertheless, older organizations would be considered to have more knowledge and experience. "The age of the firm may be considered a crude proxy for both the accumulation of experience in general and reductions in the perceived risk of investments in IT. Also, older organizations may have a consolidated image gained through the years which they are expected to maintain. The context of universities and mobile applications differs from a context of regular technology innovation, given that the adoption decision is influenced as well by the acceptance and desire of the students to have access to the innovation." (Giunta & Trivieri, 2007). Therefore, we posit the following hypothesis.

H1: Older education institutions will adopt mobile applications faster than newer institutions.

ADOPTION AND ORGANIZATION SIZE

Although authors such as Schumpeter have indicated that entrepreneurs are the most likely to innovate, cost of the adoption and its relation to available resources would relate bigger size to a faster innovation. Where cost of adoption is relatively low and therefore non relevant, smaller size could mean greater flexibility. "It is then no surprise that there exists an extensive, though inconclusive, body of empirical work on the relative innovativeness of small and large firms" (Balasubramanian & Lee, 2008). Empirical research indicates that the relationship between innovation adoption and firm size is a positive one. This is supported by the fact that larger firms are more likely and prepared to spend on innovation activities and have more available resources (Lal, 1999). It is also argued by Fabiani et al. (2005) that "the adoption of new technologies requires a firm a form of standardization of procedures and information which would limit the capabilities of small firms, whose procedures are mostly carried out on the basis of informal codes".

Organization size is an important factor for technology adoption (Pan & Jang, 2008; Cho, 2006; Yao, Xu, Liu & Lu, 2003). It is reported that larger organizations tend to adopt more innovations largely due to their greater flexibility and ability to absorb more risk (Pan & Jang, 2008; Hwang, Ku, Yen & Cheng, 2004; Zhu & Kraemer, 2005, 2003). The organization's "size" should be included in the organizational dimension (Pan & Jang, 2008). To shed light on the issue of size, we use the number of students as a unit for measuring organization size.

Another reason why larger organizations would be expected to innovate faster in the context of education institutions is the influence of users. Larger organizations will have more students. This would lead to more pressure and a higher motivation of the organization to produce an innovation. It would specially be true for innovations which are destined to be used by the students. Therefore, we posit the following hypothesis.

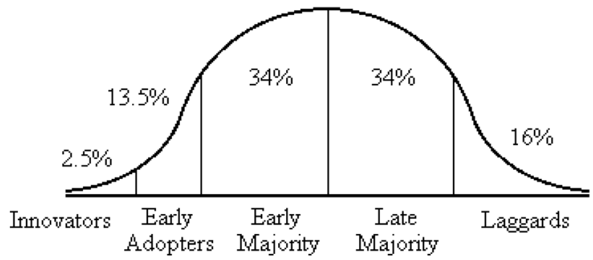
H2: Larger education institutions will adopt mobile applications faster than smaller institutions.

PREVIOUS TECHNOLOGICAL TRANSFORMATION

The concept of previous technological transformation is related to the concept of evolutionary innovation as well as to the concept of innovation behavior. Rogers introduced the innovation diffusion curve which can provide some ideas about patterns of adoption (Li, Wu, Luo, & Zhang, 2013). Arguably, firms which appear as innovators in one technology might strategically choose to be innovative. This would imply that in future adoptions they would also appear to follow an innovative behavior. Therefore, universities who were innovators or early adopters for webpages would appear as innovators and early adopters for mobile applications as well. Therefore we posit the following hypothesis.

H3 a: Education institutions who adopted a traditional web page before, will adopt mobile applications faster than those who took longer in adopting the traditional web page.

Figure 1. Rogers' Innovation Diffusion Curve.



Source: Rogers (1995) cited in (Li, Wu, Luo, & Zhang, 2013)

There would appear to be a gap in the possible interpretation of evolutionary innovation when referring to the traditional web page. That would occur due to the fact that internet is considered to be a disruptive innovation which has undergone an evolutionary innovation since its birth. Therefore, since by definition web pages would appear to be in both types of innovations, we will consider it in this paper as the previous technology used. To that sense, the transformations undergone in that previous technology will be considered of importance to the future adoption pattern of an organization. Arguably, organizations who are more conscious of updating an existing technology will be more prone to adopt a new innovation. Therefore we hypothesize the following:

H3 b: Education institutions with more average web transformations realized per year will adopt mobile applications faster than those with less web transformations.

PROXIMITY

Although proximity is initially construed as a geographic principle, the dimensions of proximity are defined by social sciences as more complex. "There is a strong need to isolate analytically the effect of geographical proximity from the other forms of proximity to determine whether geographical proximity really matters in processes of innovation" (Howells 2002).

This is a rather explicit motivation for the purpose of this paper, which will aim at quantifying the effect of only the geographical aspect. "They have pointed out that other dimensions of proximity (such as cognitive and organizational dimensions) besides geographical proximity are key in understanding interactive learning and innovation". In the 1990s, the French School of Proximity Dynamics made a key contribution to the literature on innovation when it proposed that proximity covers a number of dimensions (e.g. Torre and Gilly 2000).

For the purpose of this paper, proximity will incorporate the geographic dimension, understood as similarity and proximity between universities of a same country. Proximity in its different dimensions may also have negative impacts on innovation, due to the problem of lock-in, meaning a lack of openness and flexibility. (Boschma, 2005)

H4: Proximity will have a positive effect on the velocity of adoption of mobile applications by education institutions.

METHODOLOGY

The methodology employed consists of independent sample T-test considering the age, size, previous technology transformations and proximity. This methodology was employed due to the comparison of two sample groups. The data was sorted in relation to the age, size, number of previous web transformations and velocity of adoption of previous web adoption. The unit of analysis are universities which have adopted mobile applications and made them available to their students and/or staff members.

The variables used in the study are specified hereafter:

University	Name of the university
Foundation	Year of university foundation
Age of university	Number of years since university was founded
App Opinions (Rate)	Average Rate (1-5) downloaders assigned the application. (source www.play.google.com)
App Opinions (#)	Number of users who rated the app
App Download	Number of downloads of the app
App First Registry	Date in which the app was uploaded to google playstore
Age of app	Number of days since the app was uploaded
App Last update	Date in which the app was last updated
Today-last app update	Days since the app was last updated
App Changes	Number of updates the app received
Webpage launch	Date in which the web page was first uploaded
Age of website	Number of days since the web page was uploaded
Web Last update	date in which the web page was last updated
difference between app updates and web last updates	difference (in absolute value) between the last update of the webpage and the last update of the mobile application
Web Changes	number of changes the web page has undergone
avg changes per year	number of changes the web page has undergone divided by the number of years since the webpage was launched
web creation - app creation	number of days between the launch of the web page and the launch of the mobile application

DATA COLLECTION AND SAMPLES

A two-step data collection process was done in order to collect the required data. First, using the Google Playstore (from the Android operating system), 190 random university applications were searched up to 12/12/2013. Through the portal "AppBrain" data was collected regarding the number of downloads the application had and the average rating of the same for validation purposes. Also, the number of opinions the mobile application had and the dates in which the mobile app was created or first conceived. The number of updates that appeared and the last date of the app update were also collected. In order to determine the velocity of adoption, the dates were compared to the launch of the first mobile apps in the two main app platforms; the App Store considered being January 9, 2007 in the MacWorld Convention in the Moscone Center in San Francisco[1] and the google play store on October 22, 2008[2]. The universities were sorted according to the country location of their main campus. The second step was using the web tool "WayBack"[3], in which we obtained the number of transformations undergone by each of the universities´ webpage selected in the sample. Also, the date of the web launch was considered, and in order to determine the adoption velocity, they were compared to the first launch of the website by a university, which is dated December 12, 1991 by the Stanford Linear Accelerator Center[4].

RESULTS

The data was divided and organized by age of the university (older universities versus newer universities) in order to contrast the first hypothesis. The average launch date of the mobile application was compared between both groups. H1 was supported, given that newer education institutions in average adopted mobile applications 2186 days after the first mobile app release in contrast with older institutions who in average adopted mobile applications 2070 days after the first release. This gives empirical evidence to the proposed hypothesis that innovation adoption is faster in older institutions rather than in new ones in a context such as that of mobile application adoption by universities.

Group Statistics

	NewOld	N	Mean	Std. Deviation	Std. Error Mean
app age since release	Old	89	2054.93	342.194	36.272
	New	89	2203.58	365.293	38.721

1 Farber, Dan (2014-01-09). "When I-phone met world, 7 years ago today| Apple- CNET News". News.cnet.com. Retrieved 2014-4-25.

2 Mark Wilson (23-09-2008). "T-mobile G1: full details of the HTC Dream Android Phone". Gizmodo.com. Retrieved 2014-4-25.

3 www.web.archive.org

4 http://www.livinginternet.com/w/wi_slac.htm

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
app age since release	Equal variances assumed	.054	.816	-2.802	176	.006	-148.652	53.057	-253.361	-43.943
	Equal variances not assumed			-2.802	175.254	.006	-148.652	53.057	-253.364	-43.940

For H2, the data was organized by size (number of students) and compared between the smallest and biggest university groups. H2 was supported, given that there was significant difference between small and big universities. This result would confirm empirically that for the context of mobile applications and the education sector, size is of relevance in the velocity of adoption of innovations destined for student use. More so, this result indicates that larger universities adopt faster mobile applications than smaller universities do. Nevertheless, it would support the concept that given a larger user platform (this being number of students), this would be an incentive to provide another tool and therefore give way to a faster adoption.

Group Statistics

	SmallBigUniv	N	Mean	Std. Deviation	Std. Error Mean
app age since release	SmallUniv	83	2167.83	364.067	39.962
	BigUniv	77	2052.91	344.887	39.304

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
app age since release	Equal variances assumed	.088	.767	2.046	158	.042	114.922	56.165	3.991	225.854
	Equal variances not assumed			2.050	157.928	.042	114.922	56.051	4.216	225.628

In order to contrast H3a, the difference between the date of release of the first commercial webpage and the webpage release of each university was calculated. Then the universities were sorted and divided into two groups: those who adopted faster their website and those who adopted slower. H3a was not supported empirically by the data, indicating that there would not be a significant relation between the innovation adoption velocity of a previous a technology (website) and the velocity of adoption of a new innovation (in this case mobile applications).

Group Statistics

	FastSlowWebAdopt	N	Mean	Std. Deviation	Std. Error Mean
app age since release	FastWebAdopt	92	2138.77	332.411	34.656
	SlowWebAdopt	86	2119.08	390.444	42.103

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
app age since release	Equal variances assumed	2.870	.092	.363	176	.717	19.690	54.237	-87.349	126.730
	Equal variances not assumed			.361	167.416	.718	19.690	54.532	-87.968	127.349

To contrast H3b, the data was organized and divided in two groups. The first group had the universities who had done the least changes in their websites. The second group consisted of the universities with the most transformations done to their websites. H3b was supported, indicating that those universities who had more transformations to a previous technology (in this case their webpage), adopted the mobile application before.

Group Statistics

	LessMoreWebChYrs	N	Mean	Std. Deviation	Std. Error Mean
app age since release	LessChanges	89	2197.53	371.995	39.431
	MoreChanges	89	2060.99	337.494	35.774

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
app age since release	Equal variances assumed	.258	.612	2.565	176	.011	136.539	53.241	31.466	241.613
	Equal variances not assumed			2.565	174.359	.011	136.539	53.241	31.459	241.620

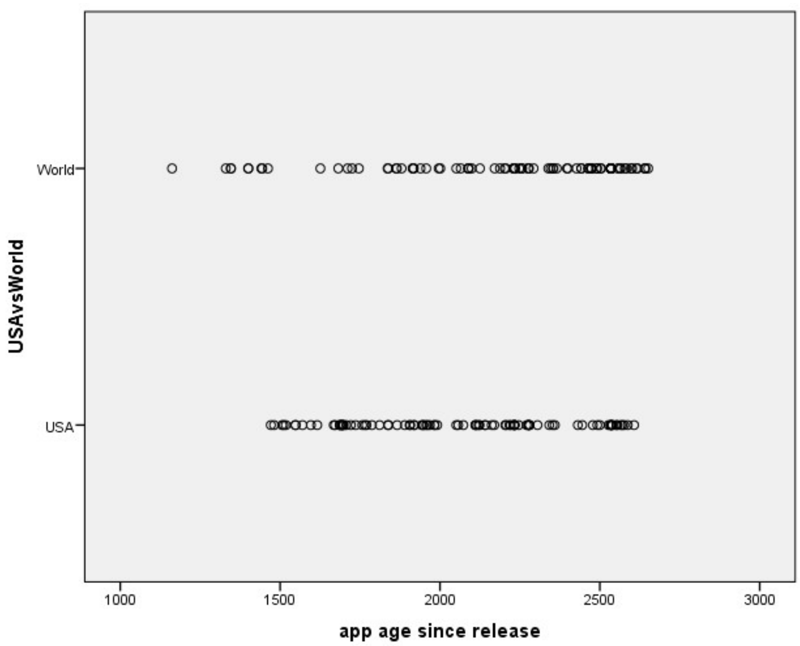
In order to contrast H4, the data was divided into two groups. The first group contained universities only from United States. The second group consisted of universities of the rest of the world. The results indicate a faster adoption of mobile applications by universities with more proximity between them in relation to universities that seem to be more apart. This gave support to H4 and indicated that proximity indeed had an effect on innovation adoption for mobile applications by universities.

Group Statistics

	USAvsWorld	N	Mean	Std. Deviation	Std. Error Mean
app age since release	USA	93	2056.33	333.305	34.562
	World	85	2209.05	374.393	40.609

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
app age since release	Equal variances assumed	.184	.668	-2.879	176	.004	-152.714	53.047	-257.404	-48.023
	Equal variances not assumed			-2.864	168.868	.005	-152.714	53.325	-257.984	-47.443



This would seem consistent with what Maskell and Malmberg (1999) affirmed: "information is transmitted more easily with cultural proximity and a common language". The results would suggest a bandwagon effect is present where the construct of proximity is higher among the universities.

Managerial Implications

The relevance of the study applies not only to university decision makers but to all organization managers. The choice to whether adopt an innovation or not will be affected by the proximity to other competitors who adopt an innovation.

A bandwagon effect indicates that once a couple few organizations have adopted an innovation, others will follow in a relatively short period of time. Therefore, it would be wise to take a similar decision where competition forces are strong and the innovation is valued most by clients (in this case students). That decision should incorporate an analysis of the positive and negative results of those organizations who previously adopted an innovation. A second managerial implication regards the adoption patterns of competitors. Given that previous technology transformations affect future innovation adoption, an organization can interpret the existence of a behavioral pattern of innovation adoption. Although this doesn´t imply that the first to innovate in a previous technology means they will be the first to innovate in a new technology. Therefore, a possible leapfrogging effect exists related to other variables such as proximity to choose the moment in which to adopt the next innovation.

LIMITATIONS & FUTURE RESEARCH

We identify some limitations to the study which could be useful to consider in future researches. One of the limitations is the number of comparisons made between universities of the same country and universities of different countries. Due to the lack of availability of official mobile apps by the universities, it was difficult to reach a large number of universities with adopted mobile apps in same countries. Other limitations were related to the data collection, where it was difficult to identify if a university had more than one mobile application available. Also, in some few cases the launch date of the mobile application was not available, and therefore, the first downloading date was used instead. Another limitation is regarding the measurement of proximity using only a geographical approach. Information regarding the target market would be an interesting future line of research, where similar target markets may affect significantly the adoption patterns of universities. Another future line of research would include the time series analysis of mobile app adoption, given it is still a relatively new market specially for the universities.

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