Anytime Autonomous English MALL App Engagement

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Abstract—Mobile assisted language learning (MALL) apps are often said to be 'Anytime' activities. But, when is 'Anytime' exactly? The objective of the paper is to provide evidence for the when of MALL activity around the world. The research method involved the collection and analysis of an EFL app's time data from 44 countries. The findings were surprising in the actual consistency of usage, 24/7, across 43 of the 44 countries. The 44^{th} country was interesting in that it differed significantly in terms of night time usage. The research also noted differences in Arab, East Asian and Post-Communist country usage, to what might be construed to be a general worldwide app time usage norm. The results are of interest as the time data findings appear to inform the possibility of a potentially new innovative pedagogy based on an emerging computational awareness of context and opportunity, suggesting a possible future language learning niche within the Internet of Things (IoT), of prompted, powerful, short-burst, mobile learning.

Keywords—CALL, MALL, EFL, IoT, Post-Communist, Saudi Arabia.

1 Introduction

'Learning anytime, anywhere' is one of the most well-known phrases used to describe learning technology [1]. A review of the Mobile Assisted Language Learning (MALL) literature will rapidly bring forth the phrase 'Anytime and anywhere.' But, when exactly is anytime? Is it really 24/7? Or, is it more nuanced? For example, does it vary from country to country, day by day or hour by hour? The literature simply does not provide answers. In many MALL research papers to date [2], [3], [4], [5], [6], [7], the word 'Anytime,' seems to refer to the unrestricted potential, 24/7, usage of MALL. There are case studies where the research refers to the time usage of small cohorts of participants [8], [9], [10], [11], although even then, little is stated about when the activities precisely occurred. Indeed, until now, there appears to have been little detailed data on when MALL activity has actually been undertaken. The idea of MALL being an anytime activity seems to be partly an inferred assumption, and partly experiential. This paper provides clear evidence of exactly when one MALL app is being used around the world.

This research is relevant, as the results could support a future of prompted, powerful, short-burst, mobile learning activities. It could also point to the development of language learning applications for interaction within the Internet of Things (IoT).

The Internet of Things (IoT) is an integrated part of Future Internet including existing and evolving Internet and network developments and could be conceptually defined as a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual "things" have identities, physical attributes, and virtual personalities, use intelligent interfaces, and are seamlessly integrated into the information network [12 p. 10].

In other words, tomorrow's worldwide network will not only have human users, but electronic device automated users [13]. The things will actually be able to communicate with other things. In addition to being context aware over great distances, it is suggested the mobile Internet will transition to an embedded Internet [14]. It is also very likely that the users will often engage with IoT locally through mobile and wearable devices, connecting to short-range smart sensors, as Broll et al. demonstrated with the Perci framework [15]. This means that IoT can provide real-time and contextualised opportunities for learners to interact with their immediate surrounding environment. This implies that learning opportunities might become available, anytime a person is active, 24/7. In fact, we have the potential to utilise context aware computing [16]. The language learning device, aware of the real world context, presents, via notification, a context and time relevant lesson at that precise moment. This transforms the catchphrase 'Anytime Anywhere' into far more meaningful 'Specific time and specific context.' Eventually, after learning more about the user's behaviour this can be drilled down to 'Most appropriate (efficient) time and most appropriate place.' However, the first step is to understand the basics of the when of 'Anytime' as highlighted in this paper. Once we establish that users are using EFL study apps 24/7, or at least for large and distinct portions of the day, then it becomes meaningful to suggest context aware computing, and IoT, may have a place in the future EFL landscape. However, if there is no concrete evidence that MALL app users are active, using applications 24/7, then why would investors and developers take on the challenge of creating language learning applications that engage IoT 24/7? IoT is expensive, and the high cost of sensors are a general barrier to implementing IoT [17]. Consequently, educational and EFL IoT will require considerable evidence to support the cost of development. This research aims to provide a partial pillar of support for that development. The role of time in contextualising the learning environment should not be underestimated, nor how local culture moulds our individual usage of time. This paper is a first step in understanding the extent to which actual MALL user behaviour indicates potential demand for interaction with the 24/7 availability of IoT and also starts the process of drilling down the specific and most appropriate when, at least, at the country level. The research also points to a specific country where 24/7 English study really means 24/7.

2 Methods

The research focused on data gathered over a 4 month period from one mobile language learning app, using Google Analytics [18], in 44 countries as shown in Table 1. Initially, data was extracted from 370,233 hourly users in 218 countries. This was gradually downsized to focus on 144,620 hourly users in 44 countries. The research also looked at 109,780 daily users in the same 44 countries and over the same time period.

The researcher was the lead developer and co-author of the app which has been recently unpublished. The app was an Android English grammar learning app which had a large user-base; 133,174 distinct devices across 218 countries were recorded accessing the app during the data collection period. The app was fairly simple, it had three distinct levels (beginner, intermediate and advanced) and one mixed level game. In addition, it provided a cheat button for quick answer review and post-game feedback on the right and wrong answer choices. The average user playing time was known to be approximately three to four minutes. The app included a terms of service and privacy statement, where it was stated that data may be gathered and used for research purposes, and users were asked to accept the terms prior to using the app. Furthermore, the extracted data was anonymous. The researcher made no attempt to tag the data to actual people. Once the data had been downloaded to the research computer, the collected and collated data was deleted from the researcher’s Google analytic account. Therefore, there is no obvious way, apparent, to associate the collated data with actual people through the misuse, or hacking into, the researcher’s accounts or computers.

In understanding the data, it should be made clear that a user, according to Analytics Help [19], is defined as a device, uniquely identified as using a specific hourly or daily segment. For example, if one person were to use five hourly segments, on ten occasions for each hour, in the data they would have been counted as five users. In other words, the user would have been defined, multiple times, as one user for each hourly segment. In fact, it is known that the 370,233 hourly users were comprised of 133,174 actual device users.

Repeat visits by a user to the same hourly segment would normally not have been counted. However, the data has certain limitations. The data can not reveal if multiple real human being users were sharing the same device; they would have been counted as one device user. So in this scenario, the research may have under-counted the number of users. Equally, it is possible that if a device has been reset, then one user could be counted multiple times, as they would receive a new unique identifying tag after each reset. In this scenario, the research may have over-counted the number of users.

The 44 countries selected for analysis were chosen using the following criteria. The country required at least 1000 hourly users, as defined above, over the four month period. This criteria narrowed the selection from 218 countries to a more manageable 64. The next phase of selection involved time comparison issues. The gathered time data was set to coordinated universal time (UTC). This data needed to be re-calculated in local time. This was achieved using world clock data [20]. However, since the data was organised in one hour chunks, any country with fractional hour time-zone differences from UTC could not be used. For example, Afghanistan is four and half hours, India is five and half hours, Iran three and half hours, Nepal is five hours and forty five minutes, Myanmar six and half hours and Sri Lanka six and a half hours, all ahead of UTC. It was not possible to use these countries as we could not accurately reproduce local time data in precise one hour chunks. Furthermore, the data collection period occurred wholly within the daylight saving summertime period and was unlikely to be a serious issue, but to enhance neighbouring country data comparability, Asian and African countries using daylight savings were eliminated from selection to increase comparability of neighbouring nations within their regions. This meant, Israel, Jordan, Morocco and Syria were removed from selection. In contrast, all of the selected European countries use daylight savings and consequently they were kept. This issue did not affect the Americas selection due to other larger complications.

Finally, there was the issue of multiple time-zone nations and nations that probably should have multiple time-zones. For example, Indonesia has three time-zones and Kazakhstan has two time-zones, these were eliminated from selection as the local time data, at country level, could not be calculated. This could have been overcome by collecting the data at city level, but this would have changed the fundamental parameters of the project. The project would have become city rather than country focused. The time-zone issue has had a huge impact on the Americas; Brazil, Canada, Mexico and the United States have had to be deselected leaving only Colombia in the data set. It has also meant that there is no representative of Oceania in the data, as Australia was deselected. This issue also affected the selection of Russia and Ukraine within Europe. In fact, the same issue affected Russia's selection within Asia too. In contrast, China and Malaysia both have singular time-zones, but a simple glance at the map of the world tells its own story. China's southern neighbours cross at least three time-zones and Malaysia's northern neighbours cross at least two time-zones. Consequently, comparing China and Malaysia with other countries would not be comparing like with like. The author knows from experience in western China, that operating on Beijing time, the local people simply start later and go to bed later, following the rhythms of the sun and not the clock. Therefore, it was decided, China and Malaysia should be eliminated from selection due to difficulties in making international comparisons. At this stage, there were 44 countries in the selection pool.

Table 1. 44 countries across 11 time-zones

Africa	UTC+	n	Asia	UTC+	n
Ghana	0	1,806	Turkey	2	3,227
Guinea	0	1,438	Saudi Arabia	3	4,871
Liberia	0	1,308	Yemen	3	1,399
Mali	0	1,875	Oman	4	1,214
Senegal	0	2,524	UAE	4	2,212
Algeria	1	2,859	Pakistan	5	7,385
Angola	1	2,400	Tajikistan	5	2,368
Cameroon	1	2,028	Turkmenistan	5	4,979
Côte d'Ivoire	1	1,653	Kyrgyzstan	6	1,751
Nigeria	1	6,916	Uzbekistan	6	14,052
Egypt	2	4,631	Cambodia	7	2,468

Libya	2	1,973	Thailand	7	4,472
South Africa	2	1,345	Vietnam	7	2,053
Ethiopia	3	7,997	Hong Kong	8	1,359
Kenya	3	1,099	Philippines	8	14,899
Somalia	3	3,668	Taiwan	8	2,460
South Sudan	3	2,163	South Korea	9	1,662
Sudan	3	6,575	Japan	9	2,988
Europe	**UTC+**	**n**	**Americas**	**UTC+**	**n**
UK[1]	1	3,393	Colombia	-5	1,303
Czech Republic[1]	2	1,060	N = 144,620		
France[1]	2	1,683	Africa		54,258
Germany[1]	2	2,237	Asia		75,819
Italy[1]	2	1,913	Europe		13,240
Poland[1]	2	1,091	The Americas		1,303
Spain[1]	2	1,863			

1. Daylight savings time

3 Results

If daily app usage was spread evenly across the 24 hours of the day, we would see a distribution of 4.2% per hour. Looking at Figure 1, we see that not one of the 44 countries breaks an hourly peak of 8% and no hourly bottom ever reaches 0%. This MALL app really does get used anytime, is surprisingly even across the 24 hours of the day, and strikingly similar across the four continents.

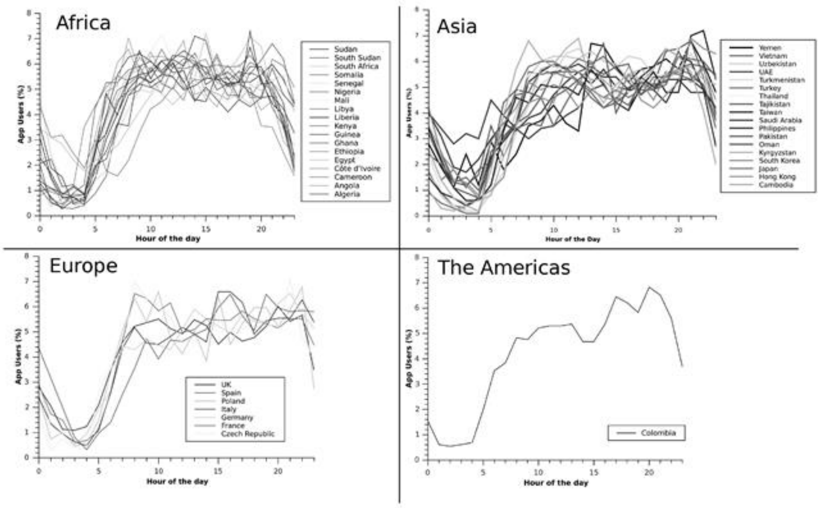

Fig. 1. Mobile app usage distribution across four continents per hour of the day

The app usage throughout the day between 08:00~22.59 is remarkably even, the lowest number of hourly users during this time period was 6,890 and the highest

8,179. Usage then falls from 5,288 during the hour 23:00~23:59 to 2,218 during the hour 01:00~01:59. The data shows that the lowest period in the 24 hour cycle is between 02:00~4:59 with an absolute low of 1,185 hourly users between 03:00~3:59. Starting at 05:00 until 07:59 activity starts to build from 2,881 users to 5,643 users. Also, while each country had its own mini-peaks, collectively there are two peak periods between 11:00~14:59 and 19:00~21:59. Please see the totals at the bottom of Appendix A for details.

Overall, the data suggests the peaks and troughs of mobile app usage follow the ebb and flow of modern life around the globe. People and app activity seem to begin to awake at 05:00 and most people are asleep, and most devices are inactive, by 02:00. The small peaks, around lunchtime and in the evening, are consistent with the expectation that more people have free-time at these times. The most interesting observation is how users find time throughout the day. The app, it appears we can confirm, was really being used anytime that the user had the time or was prompted to use it. Clearly day and evening usage, unsurprisingly, yet nevertheless can be confirmed, is much higher than late night early morning usage across all 44 countries. The day and evening data (see Appendix B) when represented as quarters, shows Q3 (12:00~17:59) to be remarkably consistent across all 44 countries with a high of 36.94% and a low of 28.05%. That said, the most unexpected take away was the number of people who do use the app in the middle of the night. In fact, approximately 8.7% of the total users (see Appendix B) were using the app in the first quarter (Q1), of the day, between midnight and 05:59. This is approximately 1 in 12 users. This nocturnal app activity was far higher than had been anticipated and, as can be seen in Figure 2, confirms that this English study app is used anytime.

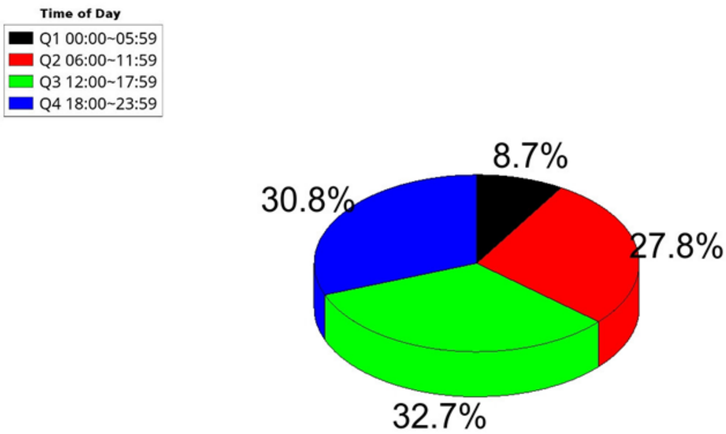

Fig. 2. 24 hour mobile app usage in quarterly 6 hour periods for 44 countries

As can be seen from Figure 1, generally all 44 countries appear to follow the same flow of daily app activity. According to Appendix B, 26 countries, late night, Q1 usage falls within a fairly narrow range of 6%~11.00%. However, the data shows that 13 of the 18 countries that fall outside of this range, belong to regional or cultural clusters that suggest a more nuanced layer of meaning in the data. For example, 11.25% of total East Asian usage occurs between 00:00~05:59, more specifically in Hong Kong (11.26%), Japan (12.42%), South Korea (12.33%) and Taiwan (9.02%). This elevated night time pattern is even more true of the Arab nations across North Africa and the Middle East. In the six hours after midnight, percentage of total usage for Algeria (9.55%), Egypt (15.57%), Libya (17.94%), Oman (12.85%), Saudi Arabia (20.84%), UAE (15.87%) and Yemen (12.29%) leads to an average after midnight usage of 14.99%. At the opposite end of the regional spectrum, according to Appendix B, the Central Asian republics have very low Q1, 00:00~5:59, usage; Kyrgyzstan (6.62%), Tajikistan (4.05%), Turkmenistan (5.00%) and Uzbekistan (6.76%) with a combined average of 5.61%.

At a glance, at Appendix B, it might appear low income countries [21], such as Cambodia (3.89%), Ethiopia (5.35%) and Tajikistan (4.05%) tend to have lower than average Q1 usage, but this cannot be fully substantiated. Guinea (10.64%), Liberia (9.25) and Mali (9.87%) are also low income nations, but have above average Q1 usage. In fact, see Table 2, national income appears to play a much smaller role in defining Q1 usage than may first appear. The data is actually relatively evenly split across the four income types. 22 countries are defined as low or lower middle income and 22 countries are defined as upper middle or high income [21]. However the low and lower middle income countries only account for 12 of the bottom 22 ranked Q1 countries and a rather significant 10 of the 22 top ranked Q1 countries. Therefore, while it is true that the data does skew towards high income greater Q1 usage and low income less Q1 usage, the finding is somewhat marginal and not persuasive.

Table 2. National income as indicator of late night usage among the 44 countries

National Income Type	Bottom 22	Top 22	Totals
Low	7	4	11
Low Middle	5	6	11
Upper Middle	5	3	8
High*	5	9	14
	22	22	44

National income data [21]
*Includes Taiwan's national income data [22].

However, there does appear to be a pattern based on a nation's current or former status as self-declared Marxist-Leninist Socialists, or more simply, communists [23]. Communist and former communist countries tend to use the English language learning app significantly less after midnight than non-communist nations. Ranking the 44 countries by Q1 usage, the post-communist nations of Angola, Cambodia, Czech Republic, Ethiopia, Kyrgyzstan, Poland, Somalia, Tajikistan, Turkmenistan, Uzbekistan, and still communist Vietnam, account for 11 of the lower ranked 22 nations. This sharply contrasts with the top 22 nations where only Yemen was once a communist country. See Table 3.

Table 3. Historical communist national identification as indicator of late night usage

Communist*	Bottom Ranked 22	Top Ranked 22	Totals
Yes	11	1	12
No	11	21	32
	22	22	44

* The term Communist refers to countries that have previously self-declared, or still do self-declare, as Marxist-Leninist socialist nations [23].

It is possible to hypothesise, given these differences, that anytime, in these 44 cases, reflects the nuance in local cultural norms and practices. Indeed, the rhythm of app usage is probably quite reflective of the rhythm of life in all 44 countries. Please see Figure 3 and Appendices B & C.

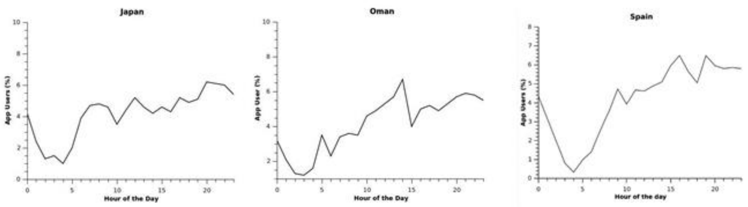

Fig. 3. Examples of nuanced mobile app usage distribution per hour of the day

Saudi Arabia, in particular, stands out when it comes to anytime 24/7 MALL. Saudi Arabian app usage, as seen in Figure 4, only fluctuates between 2.8% and 5.4% of total usage per hour, providing a range of 2.6 percentage points across the 24 hour period of the day. This is significantly less than the median average range for the 18 Asian countries of about 6 percentage points. The graph in Figure 4 is exceptionally flat in comparison to all other countries studied, see Appendix C, signifying the evenness of usage across the 24 hours of the day. The pie chart in Figure 4 reinforces this assertion of even 24 hour usage.

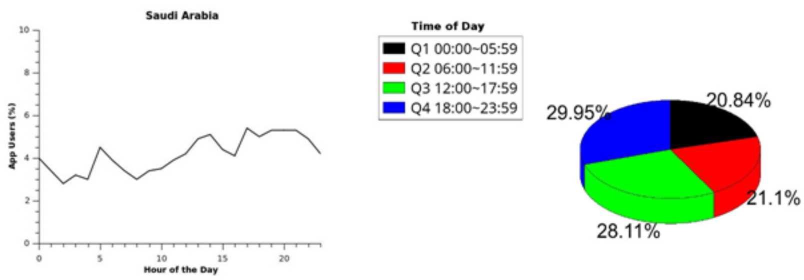

Fig. 4. Saudi Arabian 24 hour mobile app usage per hour and daily quarters

Table 4 shows the difference between global and Saudi Arabian night time usage. In Saudi Arabia users are more than three times more likely to use the app between 2:00 and 4:59 than the global average.

Table 4. Global Saudi Arabian hourly night usage comparison as percentage of 24 hr period

Location/Time	2:00 ~ 2:59	3:00 ~ 3:59	4:00 ~ 4:59	2:00 ~ 4:59
Global	1%	0.8%	0.9%	2.7%
Saudi Arabia	2.8%	3.2%	3%	9%

In taking a weekly view, see Table 5, we see little change from day to day. The daily distribution over the week is extremely even. When we look at the distribution of the 109,780 weekly users, the weekly low is 13.93% and the high is 14.76%, meaning that the range is a surprisingly low 0.83 percentage points. This means that there is no significant difference, on a global scale, between the days of the week.

Table 5. Percentage distribution of app users across 44 countries per day of the week

	Sun	Mon	Tues	Wed	Thu	Fri	Sat
Users	14.16	13.94	13.93	14.76	14.61	14.57	14.03

N = 109,780

If we focus on the individual 44 countries, see Figure 5, we do find more local variation, with daily usage from 11.58% to 17.11% of the weekly total. Over 90% of the time, the daily distribution for each country was between 13% and 16%. In precisely three quarters of cases, across the 44 countries, the distribution fell between a very narrow band of 13% to 15%. Given that 14.28% per day would provide an even distribution and a range of zero, the results are significantly and surprisingly even across the week. Please see Appendix D.

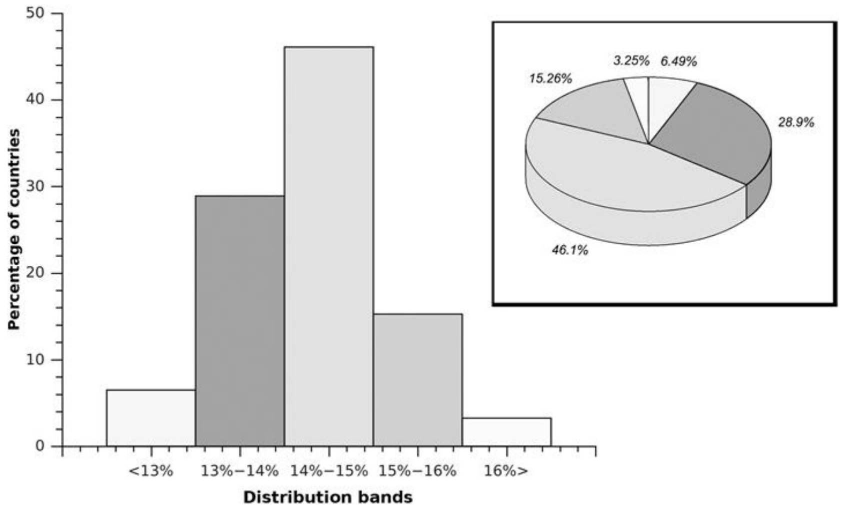

Fig. 5. Percentage of 44 countries found across per day distribution bands

4 Discussion

The results provide a concrete view of what 'Anytime' in MALL actually means. It is clear that users, from 44 countries, use the app relatively equally across the week. In terms of time of day, once again, 'Anytime' probably does literally mean anytime for at least some people in each country. While it is true, that unsurprisingly, usage tails off during the night, more surprisingly, there was never an hour when someone did not use the app in any of these 44 countries during the entire 4 month research data collection period. Whenever a person might feel comfortable using a mobile phone, it seems likely that they might be willing to study English at this time. The smallness of the range, and the relative evenness of the distribution, over the 24 hours of the day, suggests people find time for, or possibly fill time with, language learning activities. The results also suggest, that a lull in usage corresponds to sleeping activity, and peaks, where they exist, tend to correspond to traditional evening free time activity and lunchtime. This might also suggest that the app is generally used whenever a person finds that they have free-time rather than generally orchestrated by a teacher or learning environment.

Saudi Arabia provided the most interesting data with users approximately three times more likely to use the app during the four hours after midnight than the overall average. Consequently, Saudi Arabia provided a contrast with most of the other 43 countries, in that there seemed to be little distinction between day and night time usage. This suggests that Saudi Arabia could provide a unique testing environment for future EFL 24/7 research and technological development.

There appear to be two regional cultural clusters of high late night usage, in the Arab states and East Asia. A third regional cluster in Central Asia displays low late night usage, although this may be connected to a cluster based on socio-economic ideology. Former and current Marxist-Leninist socialist, or communist nations, still seem to share cultural similarities forged from their prior common ideology, and differences when compared to the rest of the world, and this is reflected in their usage of time, specifically when they decide to play an English grammar app. The why of these four distinct patterns can not be addressed in this paper, but the evidence exists to justify, and prompt, further research, and discussion, that will seek to explain these findings.

Most importantly, the results of this 'Anytime' research may inform future application development and self-study learning approaches and pedagogies. The likely time-filling environmentally prompted behaviour of the verified 24/7 app usage, may, for example, lend itself to syncing with IoT. If the evidence points to users using a grammar app at 03:00 or 15:00, then a new IoT based pedagogical model built on awareness of the user context (Where are they? What are they doing? Who are they with?) and the time that the social activity is occurring, thus means a potential timely opportunity can be created. For example, a home motion sensor, detecting movement at three in the morning, might trigger a "Since You Are Awake" learning activity. The uses are infinite, and consequently there must be a question, as we see with apps and social media today, of how users will react to a constant stream of prompts and notifications. Clearly, some will be ignored and others engaged. An understanding of the specific time, as opposed to the vagueness of anytime, of user engagement, is a vital part of honing development on the most efficient usage cases, thereby minimising the need to notify at inappropriate moments. For example, the suggested late night IoT sensor based learning activity would seem, as seen in the results (Appendix B), far more appropriate to Saudi Arabia than Cambodia. It seems probable that five times as many Saudi users would make use of this activity than Cambodians. The cost of IoT development makes it important that time specific activity hot spots are discovered and focused upon.

5 Conclusion

A nuanced global understanding of the interaction between time and local culture, within the context of glocalization, could inform a new innovative international MALL based pedagogy. The emerging computational user context awareness (when, where and what), provided by IoT, aligned with small pockets of known user app study-time, 24/7, could generate prompted, powerful, short-burst, mobile learning opportunities. These learning opportunities could be global in reach, but would be culture and user specific in terms of the when, where and what. As this study shows, time is a reachable plank of computational context awareness and a greater understanding of this could potentially intensify the impact of emerging IoT learning innovation in the very near future.

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9 Appendices

9.1 Appendix A: User totals for 44 countries per hour of the day

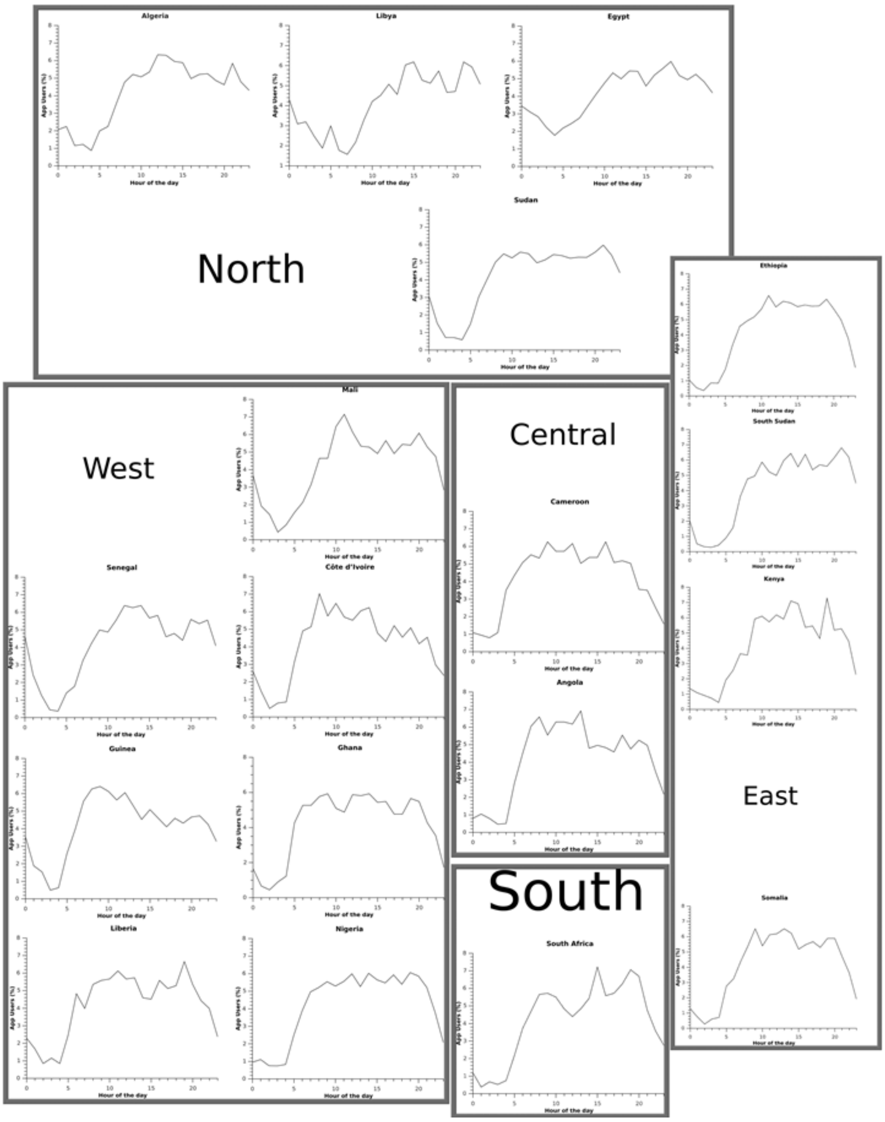
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	TOTAL
Czech Republic	18	3	8	4	5	27	39	45	74	67	64	59	48	51	48	59	50	54	58	57	54	75	51	42	**1060**
France	47	28	24	10	11	17	42	75	105	102	94	99	80	82	89	88	88	94	89	86	83	89	89	72	**1683**
Germany	66	29	21	12	21	43	59	99	96	105	100	96	114	132	123	117	111	127	121	119	137	146	128	115	**2237**
Italy	46	26	18	12	9	22	49	83	99	87	86	92	99	94	88	126	126	118	94	104	106	106	120	103	**1913**
Poland	27	8	11	5	6	16	37	55	69	59	72	52	45	55	42	70	49	58	65	65	57	64	74	30	**1091**
Spain	81	59	37	15	6	18	26	47	66	88	73	87	86	91	95	111	121	105	94	121	111	108	109	108	**1863**
United Kingdom	95	70	38	37	42	71	117	156	177	182	187	174	167	186	178	153	169	157	162	177	204	184	192	118	**3393**
Cambodia	24	7	5	9	6	45	96	141	167	151	142	142	139	132	130	118	143	129	140	161	153	138	101	49	**2468**
Hong Kong	57	33	24	16	9	14	21	49	60	63	60	77	69	81	71	59	75	61	57	64	70	94	89	86	**1359**
Japan	126	71	40	46	29	59	118	139	143	136	106	132	156	137	126	136	127	156	147	153	185	181	178	161	**2988**
Kyrgyzstan	46	25	13	8	10	14	40	62	77	99	104	114	121	90	77	89	97	99	92	92	100	101	92	89	**1751**
Oman	39	26	16	14	19	42	28	41	44	42	56	60	64	69	81	48	61	63	59	64	69	72	70	67	**1214**
Pakistan	177	146	81	63	55	182	219	268	290	343	414	410	413	432	407	425	434	346	380	381	469	397	379	274	**7385**
Philippines	228	133	99	55	98	345	431	524	780	837	877	852	886	841	799	799	732	807	864	971	920	889	723	409	**14899**
Saudi Arabia	195	166	134	155	147	218	192	164	145	165	172	190	206	239	247	215	200	262	242	258	257	259	239	204	**4871**
South Korea	58	41	23	21	14	48	60	69	87	82	85	82	69	81	76	75	91	86	75	91	93	87	94	74	**1662**
Taiwan	83	54	26	15	14	30	81	114	109	126	122	124	115	140	125	109	102	122	137	117	118	171	176	130	**2460**
Tajikistan	21	11	6	3	2	53	81	115	138	141	141	136	145	139	146	136	122	111	128	128	134	131	120	80	**2368**
Thailand	101	44	32	15	26	85	149	209	245	249	253	256	236	227	242	225	213	225	244	245	296	270	230	155	**4472**
Turkey	83	46	57	37	59	69	101	116	181	177	180	175	170	159	149	157	148	157	159	182	177	172	186	130	**3227**
Turkmenistan	119	48	20	10	9	43	84	160	212	254	276	315	322	301	306	289	311	304	276	265	281	315	276	183	**4979**
UAE	88	69	41	37	49	67	79	74	83	88	104	114	124	113	126	110	108	108	108	97	118	107	106	94	**2212**
Uzbekistan	486	253	109	39	33	30	177	370	556	755	844	869	871	862	896	838	824	738	700	712	750	810	825	705	**14052**
Vietnam	34	18	8	7	14	44	90	101	99	118	113	119	107	99	86	90	99	107	105	131	133	140	110	81	**2053**
Yemen	39	27	16	33	17	40	25	33	49	52	60	51	46	94	93	81	73	80	81	85	80	95	82	67	**1399**
Algeria	59	64	33	35	25	57	64	101	136	149	145	153	181	180	170	168	142	149	150	139	132	167	137	123	**2859**
Angola	19	25	19	11	12	67	108	145	158	133	151	151	148	166	115	119	116	110	133	114	126	119	83	52	**2400**
Cameroon	22	19	16	22	71	88	103	112	108	127	116	116	125	102	109	109	127	103	105	102	72	71	51	32	**2028**
Côte d'Ivoire	43	24	8	13	14	52	81	85	116	95	107	94	91	100	103	79	71	86	75	84	69	75	49	39	**1653**
Egypt	160	144	131	103	82	101	113	128	160	191	220	247	231	252	251	212	241	258	277	240	229	243	223	194	**4631**
Ethiopia	84	43	28	68	66	139	266	365	393	414	455	526	466	496	488	468	477	470	472	507	456	400	302	148	**7997**
Ghana	30	12	8	16	22	77	95	95	104	107	92	88	106	105	107	98	99	86	86	102	99	77	64	31	**1806**
Guinea	51	27	22	7	9	37	57	80	90	92	88	81	87	76	65	73	66	59	66	62	67	68	61	47	**1438**
Kenya	15	12	10	8	5	21	28	40	39	65	67	63	68	65	78	76	59	60	51	80	57	58	49	25	**1099**
Liberia	30	22	11	15	11	32	63	52	70	73	74	80	74	75	60	59	73	67	69	87	70	58	52	31	**1308**
Libya	85	61	63	49	37	59	35	31	43	65	83	89	100	90	119	122	104	101	113	92	93	122	117	100	**1973**
Mali	69	36	27	8	16	29	40	59	87	87	121	134	115	100	99	92	106	92	102	101	114	99	89	53	**1875**
Nigeria	66	76	52	51	57	173	268	343	360	383	366	384	414	364	416	391	378	410	373	419	405	361	263	143	**6916**
Senegal	117	61	32	11	9	35	45	82	106	126	123	140	161	158	161	143	147	116	121	111	141	135	140	103	**2524**
Somalia	47	27	10	22	26	101	119	161	198	239	198	225	227	239	228	190	201	208	194	216	216	173	133	70	**3668**
South Africa	16	5	9	7	10	29	50	63	76	77	74	65	59	65	73	97	75	77	84	95	90	64	48	37	**1345**
South Sudan	44	11	7	6	9	19	34	78	103	107	127	113	108	129	139	120	138	116	123	121	133	147	134	97	**2163**
Sudan	202	100	47	47	38	97	199	264	329	360	345	367	361	327	338	358	354	344	348	347	366	393	355	289	**6575**
Colombia	20	8	7	8	9	26	46	50	63	62	68	69	69	70	61	61	70	84	81	76	89	85	73	48	**1303**
TOTAL	**3563**	**2218**	**1447**	**1185**	**1238**	**2881**	**4255**	**5643**	**6890**	**7520**	**7805**	**8062**	**8089**	**8086**	**8026**	**7758**	**7718**	**7670**	**7700**	**8021**	**8179**	**8116**	**7262**	**5288**	**144620**

9.2 Appendix B: User percentage totals for 44 countries in six hour daily quarters

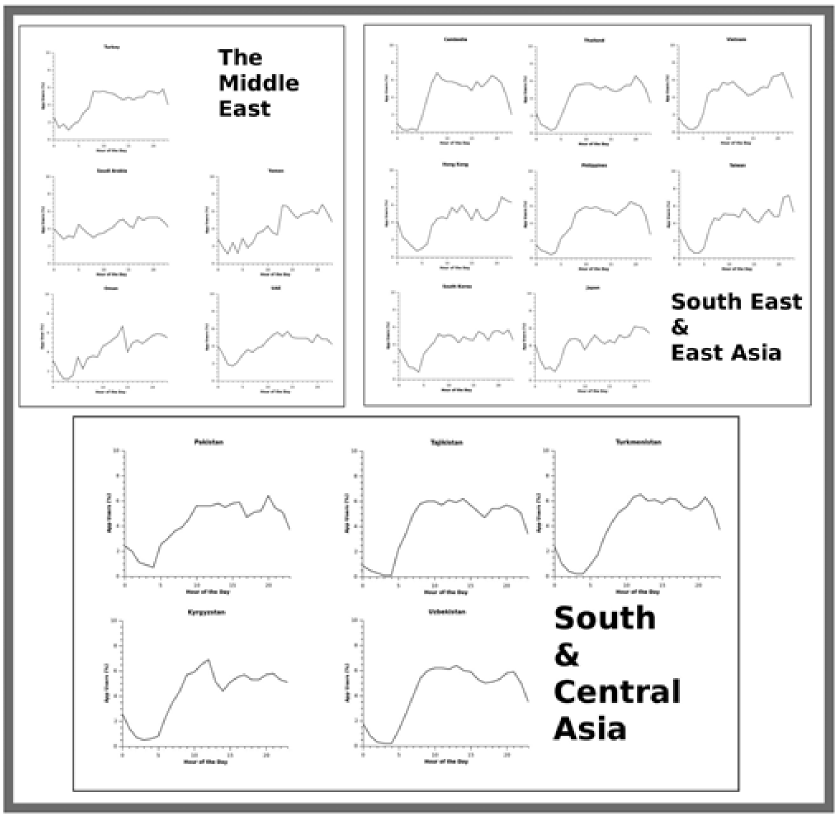
Totals		Time (%)				
Country	N =		Q1 (0.00~5.59)	Q2 (6.00~11.59)	Q3 (12.00~17.59)	Q4 (18.00~23.59)
Cambodia	2468		3.89	34	32.05	30.06
Tajikistan	2368		4.05	31.76	33.74	30.45
South Sudan	2163		4.44	25.98	34.67	34.91
Turkmenistan	4979		5	26.13	36.81	32.05
Ethiopia	7997		5.35	30.25	35.83	28.57
South Africa	1345		5.65	30.11	33.16	31.08
Colombia	1303		5.99	27.48	31.85	34.69
Vietnam	2053		6.09	31.17	28.64	34.1
Czech Republic	1060		6.13	32.83	29.25	31.79
Somalia	3668		6.35	31.08	35.25	27.32
Angola	2400		6.38	35.25	32.25	26.13
Philippines	14899		6.43	28.87	32.65	32.06
Kenya	1099		6.46	27.48	36.94	29.12
Kyrgyzstan	1751		6.62	28.33	32.72	32.32
Poland	1091		6.69	31.53	29.24	32.54
Uzbekistan	14052		6.76	25.41	35.79	32.04
Thailand	4472		6.78	30.43	30.59	32.2
Nigeria	6916		6.87	30.42	34.31	28.4
Italy	1913		6.95	25.93	34.03	33.09
Sudan	6575		8.08	28.35	31.67	31.91
France	1683		8.14	30.72	30.96	30.18
Germany	2237		8.58	24.81	32.36	34.24
Taiwan	2460		9.02	27.48	28.98	34.51
Ghana	1806		9.14	32.17	33.28	25.42
Liberia	1308		9.25	31.5	31.19	28.06
Côte d'Ivoire	1653		9.32	34.97	32.06	23.65
Pakistan	7385		9.53	26.32	33.27	30.87
Algeria	2859		9.55	26.16	34.63	29.66
Mali	1875		9.87	28.16	32.21	29.76
United Kingdom	3393		10.4	29.27	29.77	30.56
Senegal	2524		10.5	24.64	35.1	29.75
Guinea	1438		10.64	33.94	29.62	25.8
Turkey	3227		10.88	28.82	29.13	31.17
Hong Kong	1359		11.26	24.28	30.61	33.85
Spain	1863		11.59	20.77	32.69	34.94
Cameroon	2028		11.74	33.63	33.28	21.35
Yemen	1399		12.29	19.3	33.38	35.03
South Korea	1662		12.33	27.98	28.76	30.93
Japan	2988		12.42	25.9	28.05	33.63
Oman	1214		12.85	22.32	31.8	33.03
Egypt	4631		15.57	22.87	31.2	30.36
UAE	2212		15.87	24.5	31.15	28.48
Libya	1973		17.94	17.54	32.24	32.29
Saudi Arabia	4871		20.84	21.1	28.11	29.95
N =	144620	Average	8.67	27.78	32.74	30.82

9.3 Appendix C: Graphs of 43 countries from Africa, Asia and Europe

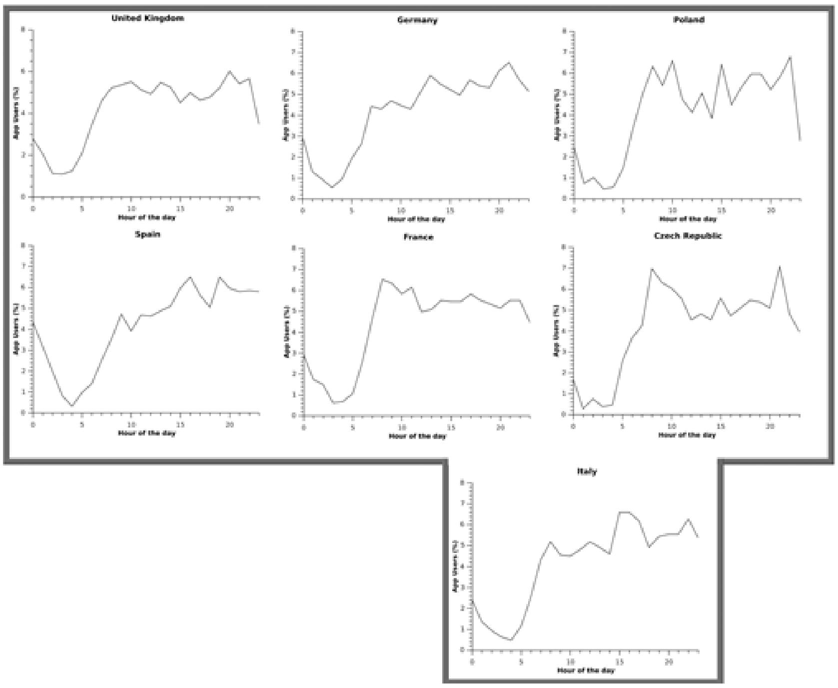
Africa



Asia


The Middle East
South East & East Asia
Pakistan
Tajikistan
Turkmenistan
Kyrgyzstan
Uzbekistan
Hour of the Day
South & Central Asia

Europe



Americas: There is only 1 nation in the Americas sample. The graph for Colombia is included in Figure 1 of the main text.

Oceania: Oceania was not included due to time-zone and sample size issues.

9.4 Appendix D: User totals for 44 countries per day of the week

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	**Total Result**
Algeria	339	340	311	337	323	320	323	**2293**
Angola	216	279	277	277	313	285	219	**1866**
Cambodia	272	265	244	262	277	289	280	**1889**
Cameroon	195	233	222	226	223	210	212	**1521**
Colombia	139	129	153	140	147	139	136	**983**
Côte d'Ivoire	181	183	166	194	205	175	155	**1259**
Czech Republic	114	125	117	125	142	122	115	**860**
Egypt	515	470	512	525	516	520	526	**3584**
Ethiopia	835	841	851	851	852	899	846	**5975**
France	191	176	200	203	194	210	171	**1345**
Germany	294	264	235	261	255	243	246	**1798**
Ghana	185	181	185	192	201	172	173	**1289**
Guinea	152	135	147	157	148	158	164	**1061**
Hong Kong	161	152	137	154	161	152	138	**1055**
Italy	203	210	205	226	194	222	219	**1479**
Japan	339	348	355	348	320	312	326	**2348**
Kenya	97	109	103	108	120	130	118	**785**
Kyrgyzstan	203	180	185	204	206	193	189	**1360**
Liberia	139	112	121	139	137	135	129	**912**
Libya	205	204	218	210	189	256	214	**1496**
Mali	204	203	197	212	204	216	222	**1458**
Nigeria	751	737	745	816	809	780	756	**5394**
Oman	129	128	135	137	128	131	137	**925**
Pakistan	823	770	763	822	795	828	817	**5618**
Philippines	1433	1413	1462	1509	1589	1494	1510	**10410**
Poland	133	139	118	134	125	129	113	**891**
Saudi Arabia	562	560	523	565	541	566	509	**3826**
Senegal	254	256	268	292	258	283	280	**1891**
Somalia	394	398	361	387	381	373	362	**2656**
South Africa	128	149	152	119	134	142	136	**960**
South Korea	202	177	192	213	189	163	172	**1308**
South Sudan	215	232	213	232	247	233	236	**1608**
Spain	207	231	204	241	210	203	197	**1493**
Sudan	652	649	665	719	686	700	666	**4737**
Taiwan	331	243	255	272	279	280	310	**1970**
Tajikistan	240	258	252	274	266	273	233	**1796**
Thailand	542	446	464	488	517	552	503	**3512**
Turkey	366	359	334	386	368	374	345	**2532**
Turkmenistan	531	505	517	570	573	566	538	**3800**
UAE	220	248	252	270	260	243	252	**1745**
United Kingdom	375	375	404	385	397	387	351	**2674**
Uzbekistan	1471	1513	1507	1605	1569	1596	1477	**10738**
Vietnam	248	227	223	231	223	207	216	**1575**
Yemen	164	148	146	183	163	135	166	**1105**
Total Result	**15550**	**15300**	**15296**	**16201**	**16034**	**15996**	**15403**	**109780**