Video Consumption with Mobile Applications in a Global Enterprise MOOC Context

Max Bothe[1], Florian Schwerer[2] and Christoph Meinel[1]

[1] Hasso Plattner Institute, Potsdam, Germany
[2] SAP SE, Walldorf, Germany

max.bothe@hpi.de, florian.schwerer@sap.com,
christoph.meinel@hpi.de

Abstract. With the proliferation of mobile devices in daily lives, users access Massive Open Online Courses (MOOCs) more often with devices other than stationary desktop computers. The introduction of mobile applications for MOOC platforms improved the learning experience by enabling Internet-independent learning sessions. Despite the university-like setting, MOOCs have also been utilized in a corporate context. Learners from different countries can integrate mobile applications into their learning process, which may result in varying usage patterns. In an observational study, the video consumption with mobile applications in different countries was examined. Based on over 2.9 million tracking events from 2019, the learning behavior was evaluated in the ten most active countries of an Enterprise MOOC platform. India and the United States showed unique patterns in terms of mobile application usage by having the highest and the lowest adoption rates. For other countries, no overarching multi-dimensional patterns were detected. In general, the use of cellular data correlates with the costs of mobile data in the respective countries. However, users who avoid cellular data do not automatically download video content to the mobile devices. Small to medium practical effects were proven for all dimensions.

Keywords: MOOCs, Mobile Learning, Enterprise MOOCs

1 Introduction

Massive Open Online Courses (MOOCs) have been proven to be effective in providing free educational resources to people with access to the Internet. They have been deployed to a variety of fields — from computer science to health-related topics [7]. Despite the original university-like setting, most MOOC learners are professionals who want to deepen their knowledge or create new job opportunities [11]. Hence, MOOCs have been utilized in a corporate context [8]. Companies offer courses, e.g., to train employees or to provide detailed documentation of their products.

Most learning activities in MOOCs are performed in a stationary setting on desktop computers [6]. However, mobile devices present a shift in traditional learning

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environments [2]. With the proliferation of mobile devices in daily lives, users accessed MOOC platforms with those devices [13]. MOOC platforms, in turn, started to optimize their user interfaces and developed dedicated mobile applications to provide a better learning experience on mobile devices [13]. With the help of mobile devices, MOOC platforms allow users to choose their preferred device for learning activities while at the same time reaching people who don't have access to desktop computers [10]. Operating with cellular networking capabilities can be both — advantage and disadvantage — for mobile devices. On one side, it allows users to escape the traditional learning setting. On the other side, broadband internet access, cellular coverage, and the respective usage rates are influenced by regional factors [10] and prices [21]. Triggered by this, mobile applications provide the functionality to download and store learning resources on mobile devices [4]. Thereby, learners also gain more options in creating their preferred learning process, being time-, device- and network-independent without leaving the designed learning environment.

Especially in a global enterprise context, learners from different countries will join the courses, thus, creating a diverse learning community. With such diversity, different usage patterns in Enterprise MOOCs will surface [5]. Analyzing learning behavior in a global context has become of increasing interest [15] as regional factors have to be considered and learning characteristics may vary. MOOC platform providers and course designers have to consider differences by adapting their technical setup and content delivery. Also, mobile devices are becoming more relevant in the corporate learning landscape [20]. To create insights on how mobile applications are used for video consumption in different countries, we formulated these research questions:

RQ1: How does the usage of mobile applications for video consumption in Enterprise MOOCs differ between countries?

RQ1a: How is the acceptance rate for mobile applications?

RQ1b: How is the acceptance rate of using a cellular connection?

RQ1c: How is the acceptance rate of downloading content beforehand?

2 Foundations

This section provides foundational information to better illustrate the underlying principles and rationales of this work. In this regard, the concepts of Enterprise MOOCs and mobile learning are introduced.

2.1 Enterprise MOOCs

The term Enterprise MOOC is used to describe online courses following xMOOC design principles, implemented in a broader business context. These courses are scalable to serve a larger audience, open to everyone, providing videos and tools for interaction, e.g., quizzes, exercises, surveys, or forum discussions, in a digital classroom over a fixed period with subsequent on-demand availability of content [14]. In contrast to Corporate MOOCs, the delivery does not exclusively focus on a company's employees but provides relevant business knowledge to all stakeholders of a company's ecosystem [8].

openSAP[1] is a digital learning platform with a focus on delivering video-based online courses. The free-of-charge offering plays an important role in SAP's continuous transformation of its education business to share knowledge about its latest innovations and relevant business or product-related topics within and beyond its global ecosystem more openly, time and device-independent, and at scale [16]. Combining short videos with additional interactive elements, and the flexibility of content consumption via desktop, mobile web, mobile applications, online or offline, Enterprise MOOCs on openSAP are an effective format for knowledge transfer in a fast-moving business context.

2.2 Mobile Learning

Research on Mobile Learning already started with the availability of the first handheld devices. Back then, studies centered around non-stationary learning methods [17]. When mobile devices became an integral part of users' lives, the focus extended to providing a ubiquitous learning experience. Compared to learning with traditional desktop computers, mobile devices offer smaller screen sizes but allow learning in non-stationary situations. Mobile applications on mobile devices are utilized to enable network-independent learning sessions [3], thus, offering a higher degree of flexibility to the users' learning process. On mobile devices, the learning behavior is influenced by various aspects — such as the device's screen size, the utilized user interface (mobile website or mobile application), or the current network connectivity state [1, 5, 12, 19]. Because of this, not all learning activities are suitable for being performed in a mobile context [9]. Learning with mobile devices should rather be considered as a complement to learning with desktop computers [18]. However, by applying Mobile Seamless Learning techniques [2], the interplay of desktop computers and mobile devices is strengthened. Here, different constraints are minimized that can influence the learning experience negatively. The ubiquitous access to learning resources is aligned this work.

3 Study Design

We conducted a long-term observational study to capture the real-world interactions of the learners with course videos on openSAP. Started video playbacks have been recorded as events using the tracking capabilities of the MOOC platform. Those tracking events are annotated with the learners' contextual environment, e.g., the used device category, operating system, and interacted content. Based on these context attributes, three different metrics have been defined and calculated — each to answer one respective research question. These metrics are discussed in more detail in Subsection 3.2. By considering only recorded tracking events, this study focused on learners who watched at least one video, while disregarding learners who didn't participate in a course (no shows). Furthermore, only the ten most active countries have been considered in this study.

[1] available at open.sap.com

3.1 Sample Data

This study is based on the users' learning activities of the year 2019 (2019-01-01 until 2019-12-31). At the end of 2019, openSAP offered 166 courses and approximately 1 million learners have been registered to the platform. Learning activities may vary depending on the offered guided MOOC courses. We acknowledge the fact that mobile usage rates evolve constantly. However, the COVID-19 outbreak in 2020 would risk distorting the recorded data disproportionately. Therefore, no data from this period was included in this study. The effects of the COVID-19 outbreak on mobile usage rates should be examined in a separate study.

3.2 Data Processing and Metric Definition

In total, over 2.9 million events for started video playbacks have been recorded in the year 2019 on openSAP. Due to this huge amount, the data processing had to be performed close to the data storage. By the means of SQL queries, each metric was first calculated for all active users. Along with that, the user's country was determined based on the IP address. If a user accessed the MOOC platform from multiple countries, only the country with the most interactions was considered. The following metrics have been defined for this study:

Adoption of Mobile Applications
Regarding RQ1a, the usage of the mobile applications had to be identified. For this, two context attributes have been utilized: *platform* and *runtime*. The *platform* attribute states the operating system of the user's device. In the case of mobile devices, this is *iOS*, *Android*, and others. This is complemented by the *runtime* attribute, which describes the accessing application. For browsers on desktop or mobile, this would be the name of the browser. Concerning the mobile applications, the value would again be *iOS* or *Android*. By these means, video playbacks with mobile applications can be distinguished from other devices or platforms. Regarding the metric, the ratio of mobile video playback to all video playbacks has been determined for each active user. A ratio of 0 indicates no usage of the mobile application, while a ratio of 1 implies that the user only consumed video with mobile applications.

Network State
As mobile devices can be connected to the Internet in different ways and offered mobile applications can operate without an Internet connection, the context of the tracking events had to be extended for these devices. The *network* attribute captures the current connectivity method when triggering new tracking events. The system can differentiate between WiFi connections, cellular connectivity, and no connection to the Internet. The connectivity method, however, does not reliably correlate to the available bandwidth. A WiFi connection has not to be sufficiently fast, and low cellular connectivity could appear as non-existent to the user. However, due to the broad cellular coverage, real offline usage of mobile applications is rare [3]. Therefore, we focus on video playbacks with a cellular connection as part of this study (RQ1b). Similar to determining the usage

rate of mobile applications, the ratio of cellular video playbacks has been determined for each active user of the mobile applications. Mobile users who avoid video playbacks with a cellular connection show a ratio of 0. Users who always rely on cellular data will have a ratio of 1.

Download Functionality
As described before, video content can be downloaded by the mobile applications to enable network independent learning sessions. To capture the respective context, the *current_source* attribute in the tracking context is utilized. This attribute is also specific to the mobile application, as other device groups (desktop web and mobile web) can only operate with an Internet connection. If the user has downloaded the video item before playback, the *current_source* attribute will hold the value *offline* and the video is loaded from the local storage of the mobile application. Otherwise, the video content is streamed over the Internet and the attribute holds the value *online*. Users might also download video content for non-offline learning sessions [3]. This is partly due to the varying network condition described as part of the previous metric. In that way, users are also prepared for possible future offline learning activities. In this study, we thus examine video playbacks with downloaded content (RQ1c). The ratio of video playbacks with an offline source has been calculated in proportion to the overall number of the user's playbacks with the mobile application. If the user always pre-downloads video content, the metric will state a value of 1. In contrast, if all video content is streamed, the ratio will be 0.

4 Results and Discussion

As a preparation for the evaluation, the countries with the highest number of active users have been determined. This study is limited to the ten most active countries of openSAP. Those countries are (in descending order of active users): India (IN), Germany (DE), United States of America (US), Great Britain (GB), Brazil (BR), Canada (CA), Spain (ES), Australia (AU), France (FR), and the Netherlands (NL). These countries combined accounted for about 69% of all started video playbacks, whereas the majority of playback events (53%) were created for users from India, Germany, and the United States.

4.1 Video Playbacks in Mobile Applications

Table 1 displays the results of the mobile application usage metric grouped for users of these ten countries along with the number of active users per country (RQ1a). India shows the highest adoption of mobile applications (14.6% of all video playbacks), while the United States registers the lowest adoption rate (3.5%). When comparing the metric results of all countries, the Kruskal-Wallis test was returned highly significant differences between the countries ($H=3596.49$; $p=<0.001$). Table 2 displays the pairwise Bonferroni corrected probabilities of the adjoining post hoc test with the respective ef-

fect sizes shown in Table 7. Based on the identified high statistically significant differences, the countries have been clustered into groups. Regarding this, countries with highly significant differences have not been placed into the groups. As a result of the general usage of mobile applications, four groups were formed. First, India shows the highest adoption rate with 10% of the users only relying on mobile applications (small to medium effect). Second, in Brazil and Australia, at least 10% of the users make use of mobile applications (small effect). Third, users from European countries (Germany, Netherlands, Great Britain, Spain, France) and Canada have a similar attitude (small effect). Fourth, the United States shows the lowest adoption rate (small effect). These groups are visualized in Figure 1. The majority of users still rely fully on the desktop environment. However, mobile applications are still utilized by users. Surprisingly, there are always users who only rely on their mobile devices for video consumption.

Table 1. Ratio of Video Playbacks on Mobile Applications

		Metric		Extreme Users	
Country	User Count	Mean	Std.Dev.	0%	100%
IN	35877	0.1460	0.3275	80%	10%
DE	25144	0.0556	0.2084	91%	3%
US	23856	0.0348	0.1662	94%	2%
GB	5839	0.0587	0.2152	91%	4%
BR	4275	0.0849	0.2542	87%	5%
CA	4122	0.0578	0.2141	91%	4%
ES	3516	0.0669	0.2249	89%	4%
AU	3233	0.0846	0.2535	87%	5%
FR	3041	0.0621	0.2234	91%	4%
NL	2976	0.0506	0.2002	92%	3%

Table 2. Video Playbacks on Mobile Applications: Pairwise Bonferroni corrected probabilities

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
DE	<0.001	-	<0.001	1.000	<0.001	1.000	0.057	<0.001	1.000	1.000
US	<0.001	<0.001	-	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.032
GB	<0.001	1.000	<0.001	-	<0.001	1.000	0.293	<0.001	1.000	1.000
BR	<0.001	<0.001	<0.001	<0.001	-	<0.001	0.111	1.000	<0.001	<0.001
CA	<0.001	1.000	<0.001	1.000	<0.001	-	1.000	<0.001	1.000	1.000
ES	<0.001	0.057	<0.001	0.293	0.111	1.000	-	0.374	1.000	0.021
AU	<0.001	<0.001	<0.001	<0.001	1.000	<0.001	0.374	-	<0.001	<0.001
FR	<0.001	1.000	<0.001	1.000	<0.001	1.000	1.000	<0.001	-	1.000
NL	<0.001	1.000	0.032	1.000	<0.001	1.000	0.021	<0.001	1.000	-

4.2 Video Playbacks with Cellular Data

For RQ1b, only users of the mobile applications have been considered. In Table 3, the data of the cellular usage metric is presented. In India, mobile users most often rely on cellular data for video playbacks (57%), whereas mobile users from Germany and Canada are more reluctant (19%–22%). The Kruskal-Wallis test revealed highly statistical differences for the usage patterns across the studied countries (H=1687.71; p=<0.001). The pairwise probabilities of the post hoc test and the respective effect sizes are shown in Table 4 and Table 8.

Table 3. Ratio of Video Playbacks with Cellular Data

		Metric		Exterme Users	
Country	User Count	Mean	Std.Dev.	0%	100%
IN	7481	0.5681	0.4328	27%	39%
DE	2321	0.2186	0.3515	62%	10%
US	1429	0.2990	0.3968	54%	17%
GB	538	0.2988	0.3918	53%	16%
BR	570	0.3377	0.4011	47%	19%
CA	386	0.1872	0.3314	66%	9%
ES	410	0.3195	0.4050	52%	17%
AU	428	0.4772	0.4393	36%	30%
FR	293	0.5035	0.4503	38%	32%
NL	253	0.2867	0.3963	57%	15%

Table 4. Video Playbacks with Cellular Data: Pairwise Bonferroni corrected probabilities

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	0.087	<0.001
DE	<0.001	-	<0.001	0.003	<0.001	1.000	0.002	<0.001	<0.001	1.000
US	<0.001	<0.001	-	1.000	1.000	<0.001	1.000	<0.001	<0.001	1.000
GB	<0.001	0.003	1.000	-	1.000	0.004	1.000	<0.001	<0.001	1.000
BR	<0.001	<0.001	1.000	1.000	-	<0.001	1.000	<0.001	<0.001	1.000
CA	<0.001	1.000	<0.001	0.004	<0.001	-	0.002	<0.001	<0.001	0.362
ES	<0.001	0.002	1.000	1.000	1.000	0.002	-	<0.001	<0.001	1.000
AU	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	-	1.000	<0.001
FR	0.087	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	1.000	-	<0.001
NL	<0.001	1.000	1.000	1.000	1.000	0.362	1.000	<0.001	<0.001	-

The countries were categorized into groups based on the highly significant differences: First, mobile users from India are the most willing to use cellular data for video streaming (small to medium effect). Second, the behavior shown in France and Australia is only slightly less in favor of cellular data usage (small effect). Here, at least

30% of the mobile users are using only cellular data. Third, the United States, Great Britain, Brazil, Spain, and the Netherlands show a similar acceptance rate (small effect). Fourth, mobile users in Germany and Canada are the least in favor of using cellular data, with 62%–66% of mobile users avoiding cellular data at all (small effect). These grouping results are shown in Figure 1. The described findings correlate with prices for cellular data in the respective countries [21]. The more affordable mobile data plans are in a country, the more users consume MOOC video content on cellular data.

4.3 Video Playbacks with Downloaded Content

Following the result of the cellular usage, the download state metric was evaluated for RQ1c (see Table 5). Also, for this metric, only users of mobile applications have been considered. In Germany, most video content was downloaded before playback (18%). In contrast, mobile users from the United States made only little use of the download functionality (9%). The applied Kruskal-Wallis test yielded highly statistical differences in usage patterns across countries ($H=102.35$; $p=<0.001$). In Table 6, the probabilities of the post hoc test are displayed, with the effect sizes shown in Table 9. The grouping process of countries based on highly significant differences resulted in three groups: First, mobile users from Germany are the most active in downloading video content, with 7% of the mobile users only consuming downloaded materials (small effect). Second, mobile users from India, Great Britain, Brazil, Canada, Spain, Australia, France, and the Netherlands all show a non-distinguishable download behavior (13%–17%; small effect). Third, most users in the United States (83%) don't consume downloaded video content (small effect). Mobile users who are more reluctant in using cellular data for video playback might be more willing to download the video content beforehand and vice versa. This assumption holds up from users from Germany and India. However, the usage patterns shown by users from the United States break the assumption. Therefore, there must be another factor influencing the users' actions, which should be discussed in future studies.

Table 5. Ratio of Video Playbacks with Downloaded Content

		Metric		Exterme Users	
Country	User Count	Mean	Std.Dev.	0%	100%
IN	7481	0.1273	0.2870	77%	6%
DE	2321	0.1771	0.3287	71%	7%
US	1429	0.0889	0.2464	83%	4%
GB	538	0.1445	0.3074	75%	7%
BR	570	0.1681	0.3187	71%	6%
CA	386	0.1537	0.3084	74%	6%
ES	410	0.1489	0.3074	74%	6%
AU	428	0.1149	0.2651	79%	3%
FR	293	0.1401	0.2927	74%	5%
NL	253	0.1209	0.2720	79%	2%

Table 6. Video Playbacks with Downloaded Content: Pairwise Bonferroni corrected probabilities

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	<0.001	<0.001	1.000	0.088	1.000	1.000	1.000	1.000	1.000
DE	<0.001	-	<0.001	0.743	1.000	1.000	1.000	0.004	1.000	0.099
US	<0.001	<0.001	-	0.005	<0.001	0.002	0.004	1.000	0.033	1.000
GB	1.000	0.743	0.005	-	1.000	1.000	1.000	1.000	1.000	1.000
BR	0.088	1.000	<0.001	1.000	-	1.000	1.000	0.168	1.000	0.693
CA	1.000	1.000	0.002	1.000	1.000	-	1.000	1.000	1.000	1.000
ES	1.000	1.000	0.004	1.000	1.000	1.000	-	1.000	1.000	1.000
AU	1.000	0.004	1.000	1.000	0.168	1.000	1.000	-	1.000	1.000
FR	1.000	1.000	0.033	1.000	1.000	1.000	1.000	1.000	-	1.000
NL	1.000	0.099	1.000	1.000	0.693	1.000	1.000	1.000	1.000	-

4.4 Overarching Usage Patterns

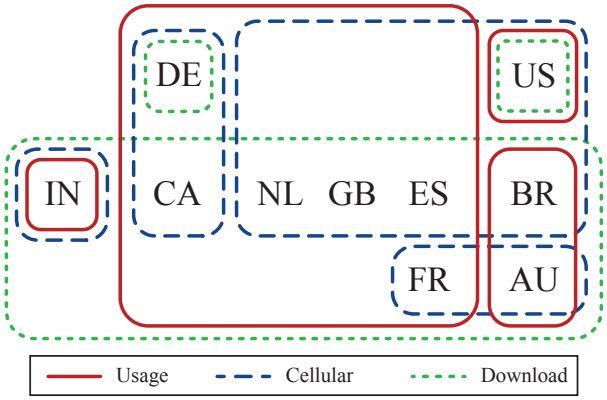

Fig. 1. Grouping of Countries with Similar Mobile Application Usage Patterns

By combing the findings from each discussed metric, we were able to visualize multi-dimensional usage patterns for video consumption in mobile applications across the considered countries (RQ1). Figure 1 shows all groups of identified countries with similar usage patterns. Hereby, each metric was encoded differently, while at the same time more general patterns become visible. Most notably, users from India and the United States show both relatively unique usage patterns. India from a separate group in terms of mobile usage and cellular usage, while the United States represents a unique group in terms of mobile usage and download behavior. For the remaining groups and countries, no overarching multi-dimensional patterns were revealed. Similar usage traits are shared across continents and no further grouping with multiple metrics can be detected. Therefore, customization and enhancements to course delivery methods for different regions should rather be made on a per-metric level.

5 Conclusion

In this observational study, we evaluated the users' usage of mobile applications in a global Enterprise MOOC context. For this, three metrics about the video playback context have been defined and applied to events tracked in 2019. Users in India showed a higher adoption rate of mobile applications compared to other countries, while users in the United States are more reluctant in their usage (RQ1a). The use of cellular data for video playbacks was in India higher, whereas users in Germany and Canada avoided the usage of cellular data. The use of cellular data correlates with the costs of mobile data in the respective countries (RQ1b). Users in Germany downloaded more videos before playback. However, users who avoid cellular data do not automatically download video content to the mobile device (RQ1c). By combining the results from all three metrics, it becomes apparent that India and the United states form unique groups in terms of mobile usage. For the remaining groups and countries, no overarching multi-dimensional patterns could be revealed (RQ1). Enhancements to course delivery methods for different regions should therefore be made for each metric individually. For all studied dimensions, small to medium practical effects could be proven. Nevertheless, we are confident that this study further contributes to a better understanding of the different aspects of how mobile applications for MOOCs are used in a global enterprise context. In turn, this allows MOOC platform providers and course designers to improve the overall learning experience.

Appendix

Table 7. Video Playbacks on Mobile Applications: Effect Sizes by Cohen's d

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	0.318	0.405	0.278	0.190	0.277	0.247	0.191	0.262	0.299
DE	0.318	-	0.110	0.015	0.136	0.011	0.054	0.135	0.031	0.024
US	0.405	0.110	-	0.135	0.275	0.132	0.184	0.278	0.157	0.093
GB	0.278	0.015	0.135	-	0.113	0.004	0.037	0.113	0.016	0.039
BR	0.190	0.136	0.275	0.113	-	0.115	0.075	0.001	0.094	0.147
CA	0.277	0.011	0.132	0.004	0.115	-	0.041	0.115	0.019	0.035
ES	0.247	0.054	0.184	0.037	0.075	0.041	-	0.074	0.021	0.076
AU	0.191	0.135	0.278	0.113	0.001	0.115	0.074	-	0.094	0.148
FR	0.262	0.031	0.157	0.016	0.094	0.019	0.021	0.094	-	0.054
NL	0.299	0.024	0.093	0.039	0.147	0.035	0.076	0.148	0.054	-

Table 8. Video Playbacks with Cellular Data: Effect Sizes by Cohen's d

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	0.842	0.630	0.626	0.535	0.889	0.576	0.210	0.149	0.652
DE	0.842	-	0.218	0.223	0.329	0.090	0.280	0.706	0.783	0.191
US	0.630	0.218	-	0.001	0.097	0.291	0.051	0.438	0.503	0.031

GB	0.626	0.223	0.001	-	0.098	0.303	0.052	0.432	0.495	0.031
BR	0.535	0.329	0.097	0.098	-	0.402	0.045	0.334	0.396	0.128
CA	0.889	0.090	0.291	0.303	0.402	-	0.356	0.740	0.817	0.277
ES	0.576	0.280	0.051	0.052	0.045	0.356	-	0.373	0.434	0.082
AU	0.210	0.706	0.438	0.432	0.334	0.740	0.373	-	0.059	0.450
FR	0.149	0.783	0.503	0.495	0.396	0.817	0.434	0.059	-	0.509
NL	0.652	0.191	0.031	0.031	0.128	0.277	0.082	0.450	0.509	-

Table 9. Video Playbacks with Downloaded Content: Effect Sizes by Cohen's d

	IN	DE	US	GB	BR	CA	ES	AU	FR	NL
IN	-	0.167	0.137	0.059	0.141	0.091	0.075	0.044	0.044	0.023
DE	0.167	-	0.294	0.100	0.027	0.072	0.087	0.195	0.114	0.174
US	0.137	0.294	-	0.210	0.295	0.248	0.230	0.104	0.201	0.128
GB	0.059	0.100	0.210	-	0.075	0.030	0.014	0.102	0.015	0.080
BR	0.141	0.027	0.295	0.075	-	0.046	0.061	0.179	0.090	0.155
CA	0.091	0.072	0.248	0.030	0.046	-	0.016	0.135	0.045	0.111
ES	0.075	0.087	0.230	0.014	0.061	0.016	-	0.119	0.029	0.095
AU	0.044	0.195	0.104	0.102	0.179	0.135	0.119	-	0.091	0.022
FR	0.044	0.114	0.201	0.015	0.090	0.045	0.029	0.091	-	0.068
NL	0.023	0.174	0.128	0.080	0.155	0.111	0.095	0.022	0.068	-

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