Log Analysis of Mobile User Behavior for a Public-Facing Math e-Learning Site

A. Nakamura

***Abstract*—Log analysis of our public-facing mathematics website has indicated a rapid increase in mobile users as a result of the increasing popularity of mobile devices. It was found that the behavior of mobile users is different from that of PC users for visitation trends, the number of page views, and searches conducted. These results suggest that our website should be optimized for mobile devices.**

***Index Terms*—e-learning, log analysis, mathematics, mobile**

I. Introduction

MANY e-commerce sites track user activities and analyze massive tracking data to provide useful recommendations and a good user experience [1]–[3], which results in improved profits. This type of data analysis is important in the competitive business world. In the case of e-learning, many educators attempt to analyze log data generated by a learning management system to assess students and improve learning environments [4], [5]. There are many websites that contain freely available useful learning materials, such as Wikipedia [6], MIT OpenCourseWare [7], and Wolfram MathWorld [8]. People use these sites on a daily basis using keyword searches and selecting links to access data. Few research studies have evaluated public-facing e-learning sites; however, a few examples are available [9]–[11]. This lack of research is due to the fact that these sites are not designed to offer learning courses, and people informally use them without logging in. Modern informal learning using Information and Communication Technology (ICT) is very important to survive in a competitive market [12].

ICT tends to cater to mobile applications due to the rapid growth of the iPhone and other mobile systems. Many mobile learning—or m-learning—methods have been proposed [13]–[15], and many users have become accustomed to frequently accessing the Internet to perform keyword searches and communicate though social media using mobile devices at any given place and time. It is expected that the rapid change in the ICT environment towards mobile devices will affect learning behavior and the use of public-facing e-learning sites.

We have analyzed the access logs of a public-facing mathematics website we developed and investigated mobile user behavior compared to PC user behavior. We will improve our Math e-learning site with the help of the research results to provide a high quality e-learning experience for both PC and mobile users. Furthermore, the results of our research will contribute to improvement of other public e-learning sites.

Manuscript received October 28, 2013.

Akira Nakamura is with the Kanazawa Institute of Technology, 7-1 Ohgigaoka, Nonoichi, Ishikawa 921-8501 Japan (phone:+81 76-248-9835; fax:+81 76-294-6832; e-mail: n.akira@ Neptune.kanazawa-it.ac.jp).

II. The Mathematics Website

A. Concept of the Mathematics Website

We have been developing the Japanese mathematics website, “KIT Mathematics Navigation,” since 2004 [16]. Typically, web pages are designed to be 800-pixels-wide for PC users. Our website provides online mathematics resource links that guide learners to what they want to learn or know. Our website has more than 1000 pages and is available to the public without login requirements. Thus, users can access our website and informally learn mathematics at their leisure.

B. Description of Mathematical Expressions

One of the technical problems of our mathematics website is the rendering of mathematical expressions. We use Mathematical Markup Language (MathML) on our original web pages. MathML, which was developed by the World Wide Web Consortium, displays mathematical expressions on web pages and enables users to transfer mathematical formulas between application software. However, not all browsers support the rendering of MathML (Mozilla Firefox and Microsoft Internet Explorer support MathML with the use of Mathplayer). Conventional Internet Explorer, Chrome, Safari, and browsers for mobile devices do not support MathML. Therefore, MathML code in HyperText Markup Language are dynamically converted to mimetex [17] code by a Common Gateway Interface (CGI) program on a server to display them as Graphics Interchange Format (GIF) images in browsers that do not support the rendering of MathML.

MathML has a number of advantages compared to other methods that usually use image files to display mathematical expressions: (1) Site maintenance is simplified by the lack of images. (2) Print quality of mathematical expressions is good. (3) Web pages are displayed faster. (4) It is easy to modify mathematical expressions because MathML tags are copied from the webpage and pasted into the MathML editor. (5) MathML allows creation of dynamic and interactive mathematical websites. The primary disadvantage is that few

DOI: 10.5176/2345-7163_1.2.25

browsers support MathML, such as browsers installed in mobile devices. Therefore, we developed CGI programs in Perl to convert MathML tags to mimetex expressions to display MathML expressions as GIF images. Our web pages are dynamically generated from original data by CGI programs. This method enables us to optimize the layout of web pages for different devices.

C. Link Back Learning

Our website has a suitable link structure for “Link Back Learning,” which is an efficient learning method where users click on a link if they want to refer to basic learning materials [18]. Each webpage has only one topic, and web pages are linked to create relationships among units of mathematical knowledge or conceptual structures of mathematics. Figure 1 illustrates “Link Back Learning” in contrast with traditional “Step by Step Learning.” We set a mathematics keyword or a mathematics key phrase suitable for a page’s topic as the page title in consideration of search engine optimization. Therefore, learners can easily reach a web page on our site based on their need (i.e., “Learning Target” webpage in Fig. 1) using a keyword search. This allows users to create their own learning path.

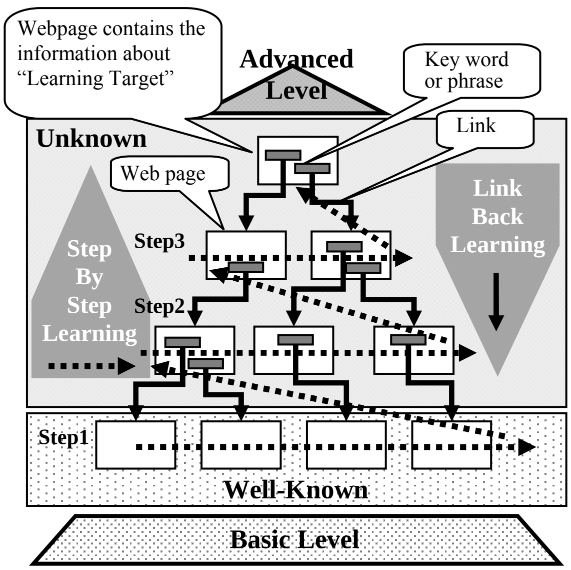

Fig. 1. Illustration of Link Back Learning

III. DATA ANALYSIS

A. Log Analyzers

We used three log analyzers, AWStats [19]. Google Analytics [20], and a custom log analyzer, to evaluate user behavior. AWStats and Google Analytics are free and powerful tools for graphically generating web server statistics. AWStats is useful to understand the outline of log statistics data. Google Analytics is able to set the duration of analysis in units of days; therefore, it is very convenient to analyze visits per day. We also developed a custom log analyzer written in PHP and MySQL to further investigate tracking data.

B. Visit Trends

Figure 2 shows that the number of monthly visits tend to increase, accompanied by periodic fluctuations. The number of visits decreases during summer, spring, and winter vacations. Figure 3 indicates the number of visits extracted in terms of four device types: Windows PC, Macintosh, iOS, and Android. Windows PC and Macintosh include desktop and laptop PC devices. iOS devices include iPhone, iPod touch, and iPad. Android devices include Android phones and tablet computers. iOS and Android device categories primarily consist of smartphones due to their high market share. The visits from iPhone users represent 83% of visits from all iOS devices in February 2013 according to Google Analytics. The number of visits using iOS devices and Android devices are similar, which have rapidly increased over the past two years. In contrast, visits from Windows devices show a decreasing trend. Figure 4 shows the ratio of visits for each device type converted from the number of visits shown in Fig. 3. Most of the increase in visits is thought to be due to the increase in visits from iOS devices and Android devices (i.e., mobile devices). Currently, approximately half of all visits come from mobile devices. This trend may be strongly related with smartphone ownership among internet users in Japan, which increased from 9.0% in September 2010 to 39.8% by October 2012 [21]. However, in Japan, page views from mobile phones were only 12.2% in July 2013 according to Startcounter [22]. The ratio of mobile traffic on our site is larger than the Startcounter data. According to a questionnaire investigation involving 300 students at our college conducted in May 2013, 31% of students have iPhones and 54% of students have Android phones. The ownership ratio of smartphones among our students is much higher than that of the Japanese general public [21]. Among students who own smartphones, the percentage that use only PCs is 3.5%, mainly PCs is 41.6%, PCs and smartphones is 31.9%, mainly smartphones is 21.4%, and only smartphones is 1.6%. This result explains the trend shown in Fig. 4.

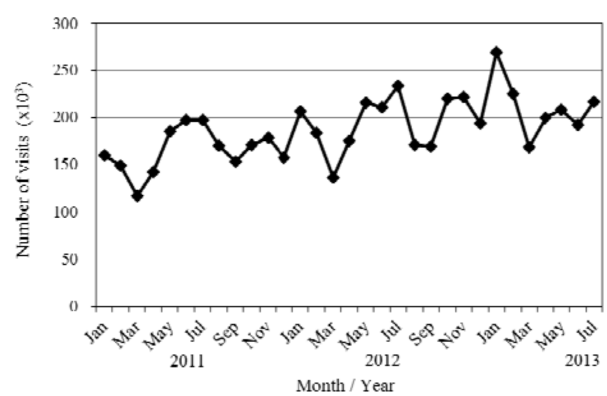

Fig. 2. Monthly visitors since 2011

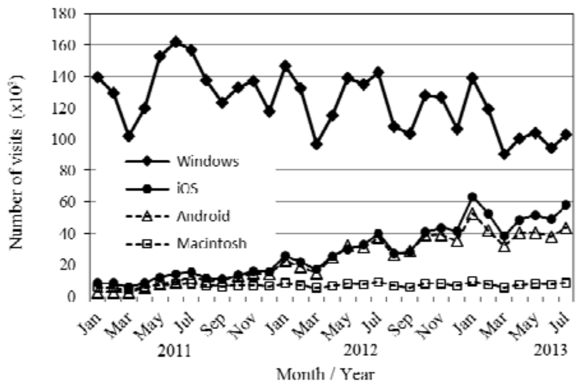

Fig. 3. Monthly visits by device type

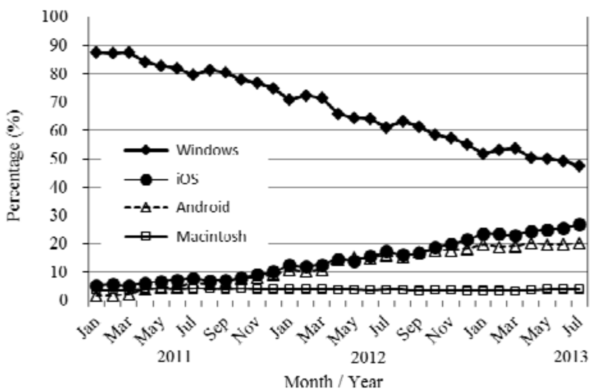

Fig. 4. Percentage of visits by device type

C. *Difference between Weekdays and Weekends*

The Windows PC trend is similar to that of Macintosh except for the number of visits. In addition, the trend for Android devices is similar to that of iOS devices. For the sake of simplicity, the data regarding Windows PCs and Macintosh are combined and categorized as PC data. The iOS and Android device data are combined and categorized as mobile data. We found that the amount of fluctuation of mobile devices is smaller than that of PCs during the week, as is shown in Fig. 5. We already knew that the number of visits have weekly periodic fluctuation [18]. To investigate the reasons for this phenomenon, we collected data from access logs gathered by the custom log analyzer. Figures 6 and 7 show the data for the co.jp and ac.jp domains, respectively. The visits from co.jp mainly consist of business people and engineers employed in Japanese companies, who use PCs in their daily work. The visits from ac.jp mainly consist of students and faculty members who use their PCs at Japanese academic organizations. The reason that visits from PCs significantly decrease during the weekend is because of the decrease of official uses, such as visits from the co.jp and ac.jp domains. On the other hand, personal use of mobile devices seems to be slightly affected on weekends. Apart from the number of visits, there is a difference in daily trends between weekdays and weekends, as shown in Figs 8 and 9. There are a large number of visits from PCs in the daytime during weekdays. During the weekend, PC visits gradually increase toward the end of the day. After-supper visits from mobile devices are fewer than those from PCs, as shown Fig. 9. This phenomenon suggests that some users switch from mobile devices to PCs to access the internet after meals at home.

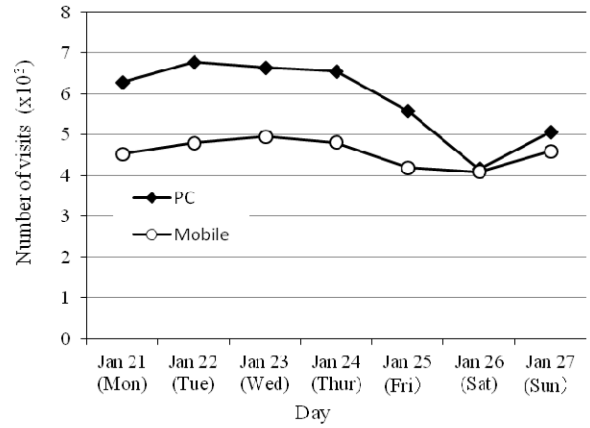

Fig. 5. Daily visits from PC and mobile devices

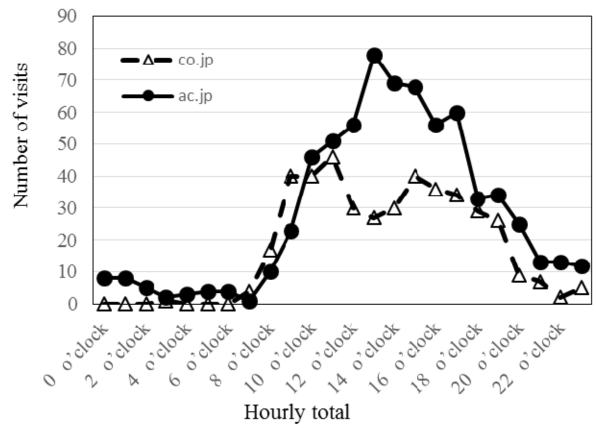

Fig. 6. Hourly visits from co.jp domain and ac.jp domain on Tuesday January 22, 2013

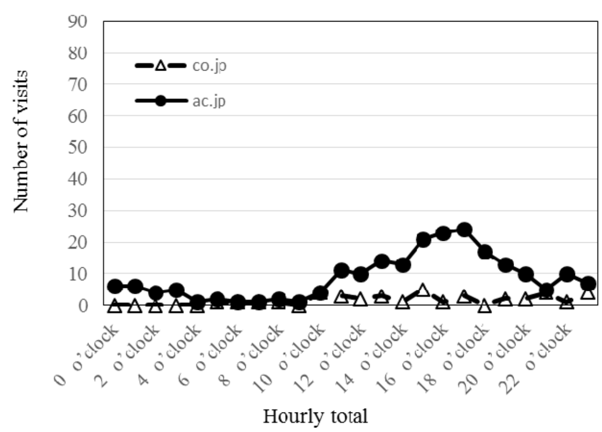

Fig. 7. Hourly visits from co.jp domain and ac.jp domain on Sunday January 27, 2013

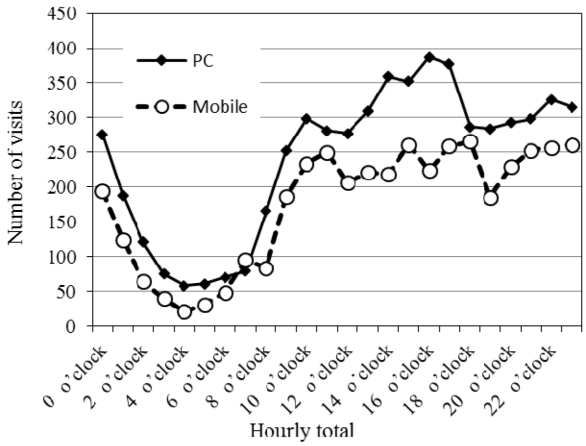

Fig. 8. Hourly visits from PC and mobile on Tuesday January 22, 2013

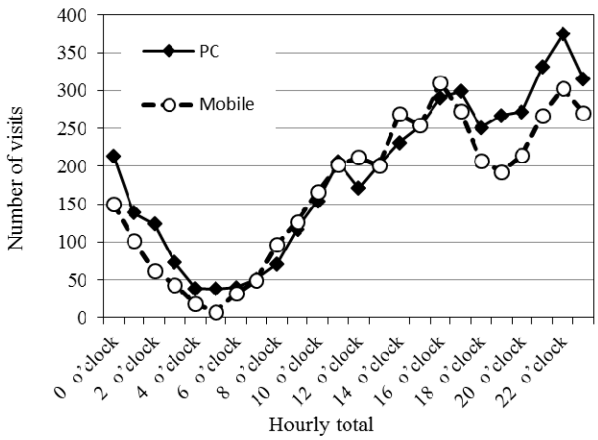

Fig. 9. Hourly visits from PC and mobile on Sunday January 27, 2013

D. Page views

Mobile users viewed more pages than PC users, as shown in Table I. iPad users viewed more pages than iPhone users, as shown in Table II. iPad and PC users produced a similar number of page views and visited more pages than iPhone users. The display size might cause this phenomenon because the user interfaces of iPhone and iPad have approximately the same functions but have different display sizes. The smartphone display size might be too small; thus, visitors may experience difficulties reading the content of our 800-pixel-wide site. Mobile users might feel stress browsing our site, resulting in lower page views, shorter visit duration, and high bounce rate. To improve mobile user experience we must redesign the CGI program and produce an optimized webpage for mobile devices.

E. Search behavior

Table III illustrates that approximately 80% of our visits come from search engines. This means that the number of visits strongly depend on the rank of the search engine, such as Google. "Direct traffic" in the table means visits coming to the site by directly typing our site's Uniform Resource Locator (URL) into a browser, following a bookmark, clicking a link in email or mobile apps, etc. Keywords and key phrases leading a visitor to our site indicate what they are searching for. Therefore, keyword analysis is a useful way to examine visitor behavior and needs. Tables IV and V indicate that, for iPhone users, direct traffic is more prevalent than search traffic, and that Android users often use search engines in a similar fashion to PC users. This difference might be attributed to the differences in behavior between iPhone users and Android users, or the differences in functions of application software between iPhone and Android devices. Accesses from iPhone devices tend to not leave referrer data. We will have to address this phenomenon in the future.

We found differences in search key phrases between mobile users and PC users. "Formula" in Japanese is the most popular search keyword leading to our site [18]. Many visitors want to know a mathematical formula by searching for it. We investigated the ratio of key phrases containing the word "formula." The result indicates that the ratio for mobile users is approximately double that of PC users, as shown in Table VI. It is thought that mobile users tend to want to know something specific about mathematics rather than wanting to learn mathematics using our site.

TABLE I
PC AND MOBILE ACCESS STATISTICS FOR SUNDAY JANUARY 27, 2013

Device	Statistical data				
	Visits	*Pages / Visit*	*Avg. Visit Duration*	*New Visits*	*Bounce Rate*
PC	42,022	3.00	0:01:56	60.99%	64.62%
Mobile	32,072	2.20	0:01:43	56.48%	71.10%

TABLE II
iOS DEVICE ACCESS STATISTICS FOR SUNDAY JANUARY 27, 2013

Device	Statistical data				
	Visits	*Pages / Visit*	*Avg. Visit Duration*	*New Visits*	*Bounce Rate*
iPad	1,536	2.76	0:02:25	59.18%	65.95%
iPhone	14,901	2.11	0:01:36	53.15%	71.06%

TABLE III
TRAFFIC SOURCE DATA FROM JANUARY 21, 2013 TO JANUARY 27, 2013

Traffic source	Number of visits	Percentage of the total visits
Referral Traffic	3,651	4.93%
Direct Traffic	12,284	16.58%
Search Traffic	58,159	78.49%

TABLE IV
TRAFFIC SOURCE BY DEVICE FOR SUNDAY, JANUARY 27, 2013

Traffic source	Device			
	iPhone	*Android*	*Windows*	*Macintosh*
Search Traffic	57.0%	83.9%	86.6%	85.5%
Direct Traffic	39.9%	9.0%	5.6%	9.5%

TABLE V
TRAFFIC SOURCE BY DEVICE FOR TUESDAY, JANUARY 22, 2013

Traffic source	Device			
	iPhone	*Android*	*Windows*	*Macintosh*
Search Traffic	53.7%	84.3%	88.0%	88.8%
Direct Traffic	42.1%	9.0%	4.7%	7.6%

TABLE VI
PERCENTAGE OF SEARCH PHRASE CONTAINING KEYWORD "FORMULA" IN JAPANESE

Day	Device			
	iPhone	*Android*	*Windows*	*Macintosh*
Jan 22	20.6%	20.1%	12.1%	11.6%
Jan 27	20.5%	22.8%	12.4%	9.5%

IV. CONCLUSION

The log analysis of our public-facing mathematics site indicates that visitor segmentation has dramatically changed during the past two years. Currently, approximately half of the visits come from mobile devices. The ratio of visits from mobile devices was less than 10% two years ago. The majority of visitors access our site from search engines. Compared to Android and PC users, iPhone users tend to access our site directly. It is difficult to determine the reasons for this difference because we cannot obtain a useful breakdown of direct traffic from log analysis. Mobile users show low weekend variations when compared with PC users. At night, some internet users switch from mobile to PC devices to browse our site. According to keyword analysis, we found that mobile users target specific mathematics formulas more often than PC users. The problem is that mobile users view fewer pages than PC users, which is possibly due to differences in screen size. Thus, we must offer an improved user experience for mobile users to increase page views.

REFERENCES

[1] M. Adnan, M. Nagi, K. Kianmehr, R. Tahboub, M. Ridley, and J. Rokne, "Promoting where, when and what? An analysis of web logs by integrating data mining and social network techniques to guide ecommerce business promotions," *Social Network Analysis and Mining,* vol. 1, pp. 173–185, 2011.

[2] C. J. Carmona, S. Ramírez-Gallego, F. Torres, E. Bernal, M. del Jesus, and S. García, "Web usage mining to improve the design of an e-commerce website: OrOliveSur.com," *Expert Systems with Applications,* vol. 39, pp. 11243–11249, 2012.

[3] N. Padhy, D. Mishra, and R. Panigrahi, "The Survey of Data Mining Applications And Feature Scope," *International Journal of Computer Science, Engineering and Information Technology,* vol. 2, pp. 43–58, 2012.

[4] H. Zhang and K. Almeroth, "Moodog: Tracking student activity in online course management systems," *Journal of Interactive Learning Research,* vol. 21, pp. 407–429, 2010.

[5] M. K. Khribi, M. Jemni, and O. Nasraoui, "Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval," *Educational Technology & Society,* vol. 12, pp. 30–42, 2009.

[6] *Wikipedia*. Available: http://en.wikipedia.org/wiki/Main_Page

[7] *MIT OpenCourseWare*. Available: http://ocw.mit.edu/index.htm

[8] *Wolfram MathWorld: The Web's Most Extensive Mathematics Resource*. Available: http://mathworld.wolfram.com/

[9] D. Shen, X. Wang, and H.-L. Chen, "Managing Web-based Learning Resources for K–12 Education: Lessons Learned from Web Analytics," in *World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, Las Vegas, Nevada, USA, 2008, pp. 470–475.

[10] D. Ellis, "Google Analytics as a tool in the development of e-learning artifacts: A case study," in *ascilite Conference*, Wellington, New Zealand, 2012, pp. 299–303.

[11] W. Fang, "Using google analytics for improving library website content and design: a case study," *Library Philosophy and Practice,* 2007, pp.1–17. Available:http://www.webpages.uidaho.edu/~mbolin/fang.pdf

[12] M. D. Enos, M. T. Kehrhahn, and A. Bell, "Informal learning and the transfer of learning: How managers develop proficiency," *Human Resource Development Quarterly,* vol. 14, pp. 369–387, 2003.

[13] C. K. Looi, P. Seow, B. Zhang, H. J. So W. Chen, and L. H. Wong, "Leveraging mobile technology for sustainable seamless learning: a research agenda," *British Journal of Educational Technology,* vol. 41, pp. 154–169, 2010.

[14] A. Nakamura, "The development of math learning materials: Integrating print materials and web materials utilizing a mobile phone," in *IADIS International Conference Mobile Learning 2010*, Porto, Portugal, 2010, pp. 393–396.

[15] A. Nakamura, "Math Learning Materials Combining Print Materials and Web Based Training," in *2011 14th International Conference on Interactive Collaborative Learning (Icl)*, Piestany, Slovakia, 2011, pp. 214–217.

[16] *KIT mathematics navigation*. Available: http://w3e.kanazawa-it.ac.jp/math/

[17] *Mimetex*. Available: http://www.forkosh.com/mimetex.html

[18] A. Nakamura, "Usage analysis of the free math learning site," in *Shanghai International Conference on Social Science*, Shanghai, China, 2012, pp. 666–673.

[19] AWStats - Free advanced log file analyzer for web, ftp or mail statistics (GNU GPL). Available [13]: http://awstats.sourceforge.net/

[20] Google Analytics Official Website. Available: https://www.google.com/analytics/

[21] *Research on the Trend of Use of Cell phone and Smartphone*. Available: http://www.impressrd.jp/news/121120/kwp2013

[22] *Startcounter*. Available: http://gs.statcounter.com/

[23] A. Nakamura, "Smartphone Effect on Usage Behavior of Math Web Site," in *61st Annual Japanese Society for Engineering Education Conference*, Niigata, Japan, 2013, pp. 2–3.

Akira Nakamura was born in Japan in 1961 and received his Master of Engineering degree from Osaka University in 1986.

He joined the Matsushita Electric Industrial Co., Ltd. (Panasonic) in 1986 and was engaged in the research and development of the lucid crystal display. He joined the Kanazawa Institute of Technology in 2004 and presently holds the rank of professor. He has been engaged in teaching mathematics and physics, and in the research and development of e-learning.