Motivation for learning in massive open online courses differs according to the learners' socioeconomic backgrounds:
Meta-analytical results of synthesizing seven courses

Takayuki Goto (School of Human Cultures, The University of Shiga Prefecture, goto.t@shc.usp.ac.jp)
Mana Taguchi (Center for the Promotion of Excellence in Higher Education, Kyoto University, taguchi.mana.3z@kyoto-u.ac.jp)

学習者の社会経済的背景による大規模公開オンライン講座 (MOOC) 受講動機の違い
—7 つのコースのデータを用いたメタ分析的検討—

後藤 崇志（滋賀県立大学 人間文化学部）
田口 真奈（京都大学 高等教育研究開発推進センター）

要約

近年、インターネット上で学びを進めることが可能な大規模公開オンライン講義（MOOC）と呼ばれる形態の講義が広まっている。本研究では受講者の社会経済的背景と内発的動機づけ・外発的動機づけの高さとの関連を検討した。研究1では1つのコースの受講者1,633名から得られた質問紙データを分析し、国民1人あたりの国内総生産（GDP）が低い国からの受講者は外発的動機づけが高い傾向にあることが示された。研究2では、研究1で扱ったコースを含めた7つのコースのデータについてメタ分析的手法を用いて検討を行った。その結果、国民1人あたりの国内総生産（GDP）が低い国からの受講者は内発的動機づけが低く、外発的動機づけが高い傾向にあることが示された。また、ジニ係数が高く、経済格差の大きい国からの受講者は外発的動機づけが高い傾向にあることも示された。以上より、社会経済的にあまり富んでいない国からの受講者は、MOOCを通じてキャリアを向上させようとするような外発的動機づけが高い傾向にあることが示された。これらの結果を踏まえ、MOOCに期待される役割のひとつである、教育機会の格差是正の実現可能性について論じる。

Key words
learning motivation, massive open online courses, gross domestic product, gini coefficients, economic inequality

1. Introduction

Over the past few years, many educational courses, referred to as Massive Open Online Courses (MOOC), have become available on the Internet. MOOC provide people with the opportunity to expand their education anywhere and anytime, and MOOC are attracting millions of learners to enroll freely in their courses. In the beginning, the mass media sensationally reported the massiveness of MOOC (Selwyn, Bulfin, & Pangrazio, 2015). However, more recently, the main topics of mass media have been moving away from massiveness to the qualitative aspects of MOOC (Kovanović, Joksimović, Gašević, Siemens, & Hatala, 2015). The majority of the mass media discuss how MOOC can change existing educational systems.

One of the expected roles of MOOC is to minimize social inequality by providing educational opportunities to those who could not access higher education earlier (Friedman, 2012). Contrary to these expectations, however, research has revealed that most MOOC learners possess advantageous socioeconomic backgrounds, such as being well educated (Ho, Reich, Nesterko, Seaton, Mullaney, Waldo, & Chuang, 2014; Perna, Ruby, Boruch, Wang, Scull, Ahmad, & Evans, 2014) or living in wealthier areas (Hansen & Reich, 2015). Some researchers doubt whether MOOC can realize their ideals, that is, to minimize social inequality (Emanuel, 2013).

The present research addresses this issue by exploring the relationship between the qualitative aspects of learners' motivation and economic inequality. One of the most attractive aspects is the viewpoint of intrinsic or extrinsic motivation (Ryan & Deci, 2000). Intrinsic motivation refers to engaging in the learning process because of finding it interesting, enjoyable, and improving one's competence. On the other hand, extrinsic motivation refers to engaging in the learning process because of expecting external rewards or wanting to avoid punishments.

MOOC is a form of informal learning, where learners enroll in courses outside of the formal school curriculum. Informal learning is considered to be learner-led and intrinsically motivated, rather than teacher-led and extrinsically motivated, as with formal learning (Rennie, 2007). Both qualitative and quantitative research have shown that the audience members of informal science events were mainly intrinsically motivated learners (e.g., AbiGhannam, Kahlor, Dudo, Liang, Rosenthal, & Banner, 2015; Goto, Nakanishi, & Kano, 2018). As for MOOC, researches have revealed that MOOC learners are also mainly motivated by intrinsic factors (Barak, Watted, & Haick, 2016; Kizilcec & Schneider, 2015). This indicates that learners in MOOC are likely to be people who are primarily motivated to learn by intrinsic factors.

However, the reasons why learners enrolled in MOOC may vary by their backgrounds. Some would be motivated by extrinsic factors, such as improving their own career prospects. In the present research, we investigate the relationship between MOOC learners' motivation and their socioeconomic backgrounds. Some research has focused on the proportion of the learners with different socioeconomic backgrounds (Hansen & Reich, 2015; Ho et al., 2014; Perna et al., 2014), but none have tested the relationship between these backgrounds and their motivations. If learners from disadvantageous socioeconomic backgrounds are more motivated to improve their own career prospects via enrollment in MOOC, we can infer that they believe that MOOC can pull up them to a higher social class, not simply supply them with stimulating experiences. We can attribute this to the potential of MOOC as a means to minimize social inequality.

2. Study 1

In Study 1, we analyzed the data of "*KyotoUx 001x – The Chemistry of Life (001x)*," which was an MOOC course offered by Kyoto University from April 9, 2015 to July 22, 2015. This course aimed to develop skills for generating new ideas at the interface between chemistry and biology by analyzing pioneering studies.

The research aims were to test the relationship between students' learning motivations and their socioeconomic backgrounds. Learners' socioeconomic backgrounds were estimated by gross domestic product (GDP) per capita and Gini coefficients, which is widely known as the index of economic inequality within a country (Gini, 1936).

2.1 Respondents

From April 9 (the start of the course) to July 22 (the end of the course), 1640 learners took part in the pre-course survey.

2.2 Measures

2.2.1 Learning motivation

Based on some of the previously developed motivation scales (Asano, 2002; Goto, Kudo, Mizumachi, & Kano, 2014) and prior research on MOOC (e.g., Zheng, Rosson, Shih, & Carroll, 2014), we developed learning motivation scales for MOOC consisting of 10 items (Taguchi, Goto, Mohri, & Iiyoshi, 2017). In this scale, the 10 items focus on some of the goals that learners are most likely to pursue throughout the course (e.g., "to satisfy my curiosity," "to enhance my employability skills," and "to connect with people who I share interest with"). Learners responded to each item on a 7-point scale, ranging from 1 ("Strongly disagree") to 7 ("Strongly agree").

2.2.2 Socioeconomic backgrounds

As the respondents' IP address were collected via the pre-course survey, we identified where they currently live at a country level. Then, we obtained the Gini coefficients and GDP per capita in US$ from the most recent statistics reported by the World Bank (2015).

2.3 Results

2.3.1 Preliminary analysis: Factor structure of leaning motivation scale

First, we conducted the exploratory factor analysis for eight items of the learning motivation scale with maximum likelihood extraction and oblimin rotation. We omitted two items from the analysis. Item 3 "To obtain deeper understanding of Chemistry and Biology" was omitted, as the description was specialized to this course. Item 10 "To check out a Kyoto University course" was also omitted, as this item was created for another purpose and not intended for use in analyzing learners' motivation.

According to the results of parallel analysis, we extracted two factors from these eight items. The factor loadings are reported in Table 1. As factor 1 had strong loadings on items referring to career or applicability, we interpreted this factor as "extrinsic motivation." As factor 2 had strong loadings on items referring to curiosity or enjoyment, we interpreted this factor as "intrinsic motivation."

For the following analysis, we calculated the subscale scores of intrinsic motivation and extrinsic motivation. Intrinsic

Table 1: Factor loadings in exploratory factor analysis of learning motivation scale (Study 1)

	Items	Factor loadings	
		Factor 1	Factor 2
1	To satisfy my curiosity	–.050	.714
2	To connect with people who I share interest with	.411	.240
4	To apply knowledge in real-life situations	.526	.282
5	To enhance my employability skills	.838	-.091
6	To advance my academic career	.846	-.068
7	To obtain specific skills/knowledge	.557	.273
8	To enjoy myself and have fun	.007	.726
9	To obtain the course certificate	.512	.021
	Factor correlation	.190	

motivation was calculated by averaging the responses of items 1 and 8. Extrinsic motivation was calculated by averaging the responses of items 5, 6, and 9. Items 2, 4, and 7 were not used to calculate subscale scores, as these items highly loaded both the factors. Respondents tended to mark a higher score on intrinsic motivation (M = 6.11, SD = 1.12) than extrinsic motivation (M = 4.46, SD = 1.68).

2.3.2 Country-level correlation between learning motivation and socioeconomic backgrounds

We identified that the 1640 learners had accessed the course from 112 countries. First, we calculated the average values of intrinsic and extrinsic motivation scores by respondents' countries of residence (Figure 1). Then, we estimated the country-level correlation between the values for learning motivation and socioeconomic background. As reported in Table 2, intrinsic motivation was neither significantly correlated with GDP per capita nor with Gini coefficients. On the other hand, extrinsic motivation was negatively correlated with GDP per capita, but not with Gini coefficients. These results indicate that learners from disadvantageous socioeconomic backgrounds were more highly motivated by extrinsic reasons.

Table 2: Country-level correlation between learning motivation, GDP per capita, and Gini coefficients in Study 1

		1	2	3	4
1	Intrinsic motivation				
2	Extrinsic motivation	.11[a]			
3	GDP per capita	.04[b]	–.24*[b]		
4	Gini coefficients	–.06[c]	.09[c]	–.36*[c]	

Note. * p < .05. As the dataset contained some missing values, we calculated the correlation coefficients with pairwise deletion ([a]n = 112, [b]n = 92, and [c]n = 82).

3. Study 2

The results of Study 1 indicated that learners from disadvantageous socioeconomic backgrounds are more motivated to improve their own career prospects via enrollment in MOOC. However, these results were led by analyzing the learners' data of only one course. We need to confirm whether such a tendency can be observed in other courses.

In Study 2, we analyzed the learners' data of six other courses provided during the 2015 academic year. Then, we combined these results and those of Study 1 by using the meta-analytical method. This procedure can provide more robust evidence for the relationship between learning motivation in MOOC and socioeconomic backgrounds.

3.1 Procedures

We analyzed the learners' data of six courses. Information about respondents, the targeted courses, and data collecting are reported in Table 3. As learners responded to the same learning motivation scales to "001x," we calculated the country-level scores of intrinsic and extrinsic motivations, as in Study 1. We also identified the learners' countries of residence and their country-level socioeconomic backgrounds, as in Study 1. We calculated the meta-analytical correlation coefficients by meta package of R.

3.2 Results

Correlation coefficients between learning motivation and GDP per capita are reported in Table 4. Meta-analytical results indicated that intrinsic motivation was positively correlated with GDP per capita (ρ =.11, 95 % CI = [.03, .20]). On the other hand, extrinsic motivation and GDP per capita were negatively correlated in all seven courses. Meta-analytical results also showed that extrinsic motivation was negatively correlated with GDP per capita (ρ = –.26, 95% CI = [–.35, –.18]).

Next, we tested the relationship between learning motivation and Gini coefficients. Correlation coefficients are reported in Table 5. Consistent to the results of Study 1, intrinsic motivation and Gini coefficients were not significant in most of the courses. Meta-analytical results indicated that there was almost no relationship between intrinsic motivation and Gini coefficients (ρ = –.04, 95 % CI = [–.14, .05]). On the other hand, extrinsic motivation and Gini coefficients were positively correlated in most of the courses. Meta-analytical results showed that extrinsic motivation was positively correlated with Gini coefficients (ρ =.26, 95 % CI = [.10, .41]).

By analyzing the learners' data of six MOOC courses, we obtained more robust results about the relationship between learning motivation and socioeconomic backgrounds. We replicated the results of Study 1, that learners from disadvantageous socioeconomic backgrounds were highly motivated by extrinsic reasons. We were able to confirm the robustness of these tendencies by using meta-analytical method.

4. Discussion

We analyzed the learners' data of seven MOOC and revealed that learners from disadvantageous socioeconomic backgrounds were highly motivated by extrinsic reasons. Some research has focused on the proportion of MOOC learners with different socioeconomic backgrounds (Hansen & Reich, 2015; Ho et al., 2014; Perna et al., 2014), but none have tested the relationship between these backgrounds and learners' motivations for learning via MOOC. As far as we know, this is the first study to show that learning motivation in MOOC can vary among learners from different socioeconomic backgrounds.

These results indicated that MOOC have a certain amount of potential as a means to minimize social inequality. The results showed that learners from disadvantageous socioeconomic backgrounds were more motivated to improve their own career prospects via enrollment in MOOC. We can infer that MOOC

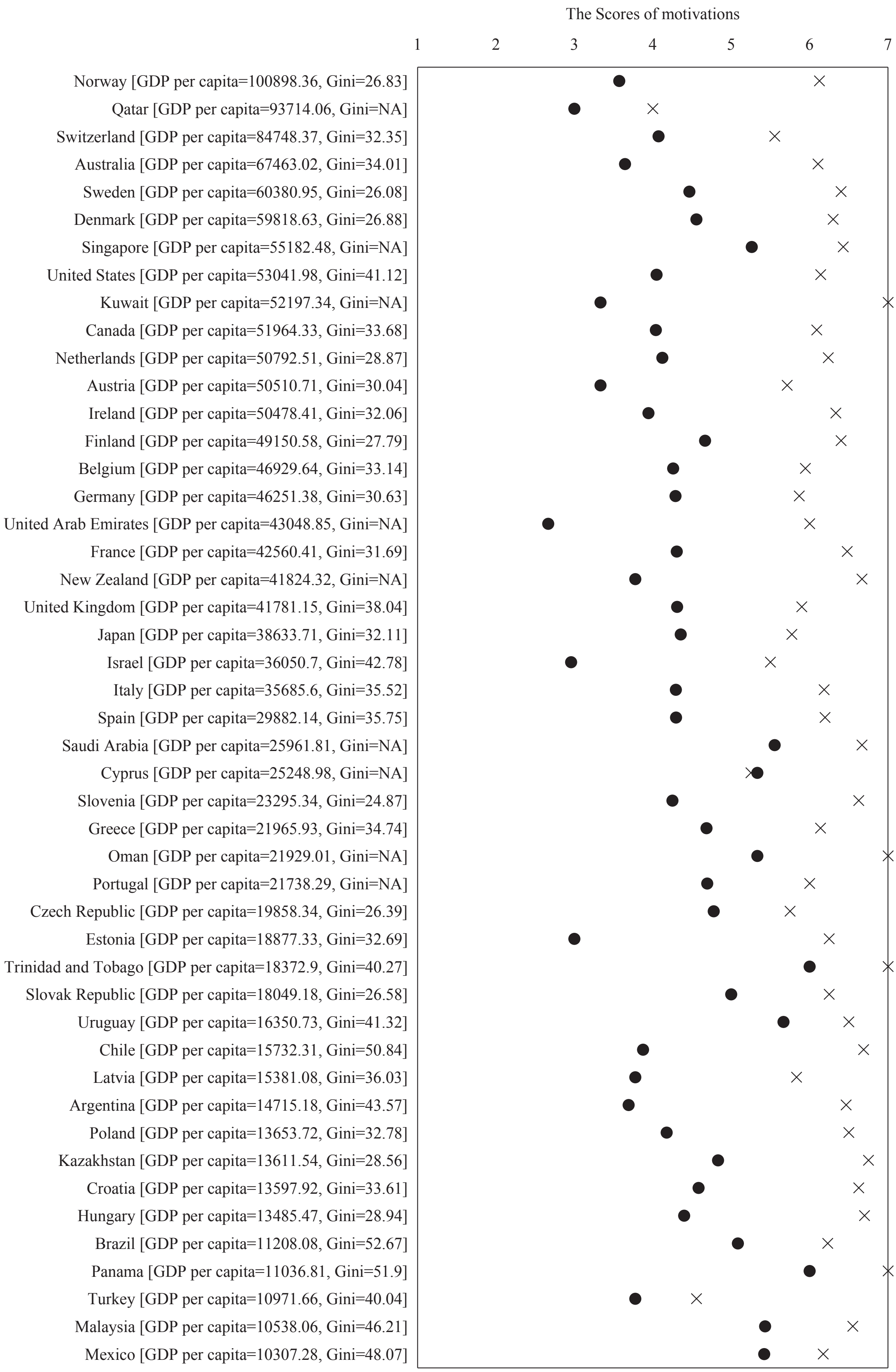

Figure 1: Average values of intrinsic and extrinsic motivation by respondents' country of residence in Study 1

Note: Countries are sorted by GDP per capita. Cross marks refer to the scores of intrinsic motivations, and black circles refer to the scores of extrinsic motivation.

(Figure 1: Continues)

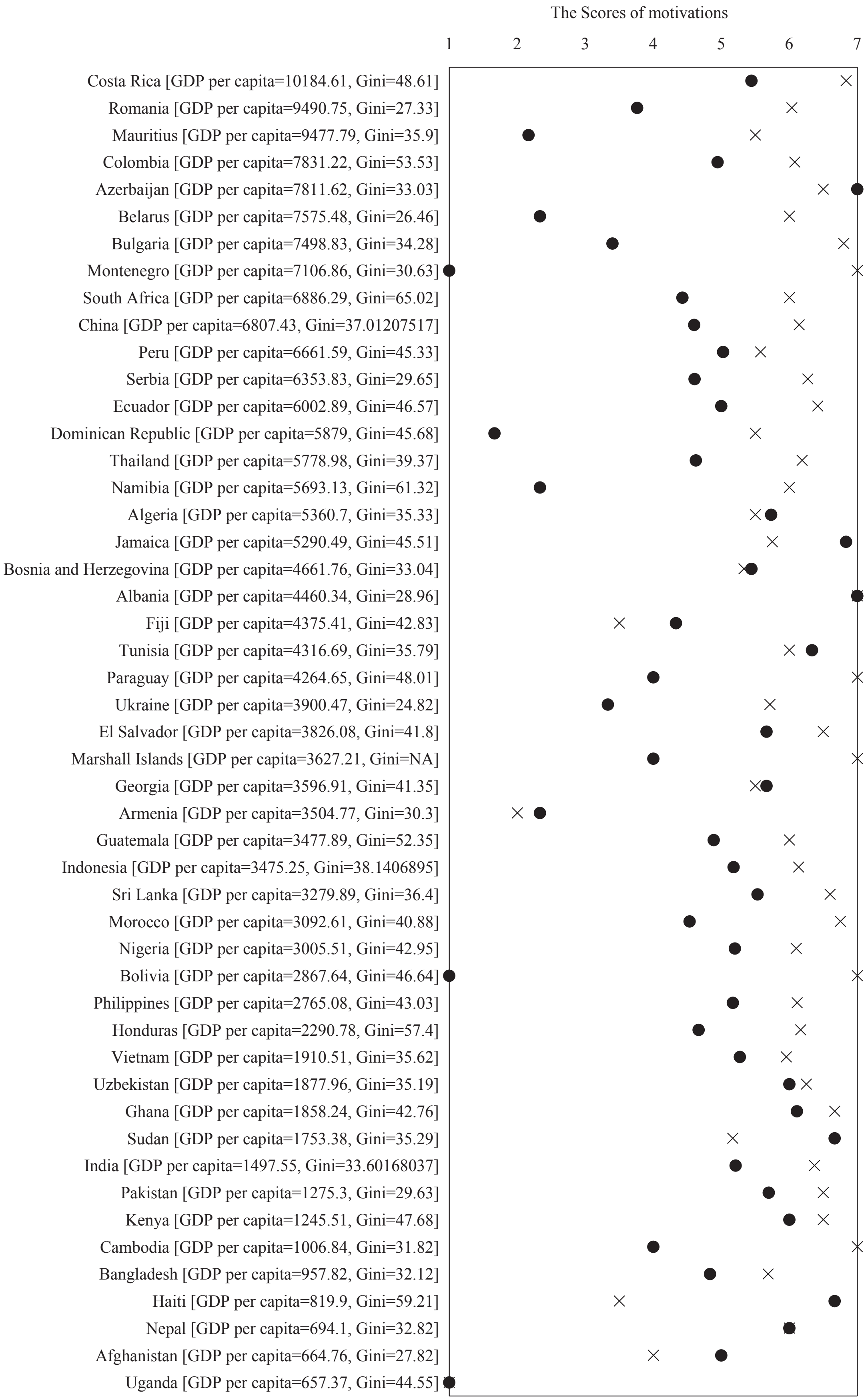

Table 3: Summary of the targeted courses and data collection in Study 2

Course		Numbers of respondents	Numbers of identified countries
000x	Evolution of the Human Sociality: A Quest for the Origin of Our Social Behavior	450	68
001x	The Chemistry of Life	1,640	112
002x	Culture of Services: New Perspective on Customer Relations	750	99
003x	The Extremes of Life: Microbes and Their Diversity	596	82
004x	Fun with Prime Numbers: The Mysterious World of Mathematics	1,788	104
005x	Introduction to Statistical Methods of Gene Mapping	296	65
006x	Ethics in Life Sciences and Healthcare: Exploring Bioethics through Manga	263	55

Table 4: Correlation coefficient and sample size of the scores of learning motivations and GDP per capita in each course

Course	Intrinsic motivation		Extrinsic motivation	
	r	*n*	*r*	*n*
000x	.30	62	–.21	62
001x	.04	96	–.24	96
002x	.04	85	–.36	85
003x	.18	72	–.39	72
004x	.07	86	–.21	86
005x	.13	57	–.17	58
006x	.13	49	–.17	49

Table 5: Correlation coefficient and sample size of the scores of learning motivations and Gini coefficients in each course

Course	Intrinsic motivation		Extrinsic motivation	
	r	*n*	*r*	*n*
000x	–.06	53	.03	53
001x	–.05	86	.09	86
002x	–.12	73	.37	73
003x	.07	63	.27	63
004x	–.22	74	.18	74
005x	.13	50	.22	51
006x	.10	40	.62	40

learners in disadvantageous socioeconomic backgrounds expected MOOC would be a useful means for career enhancement, and did not simply enroll for stimulating experiences.

While it has not been directly tested in a statistical way whether enrolling in MOOC could improve one's own career, some institutes have strived to make MOOC a meaningful opportunity for those who want to. For example, some courses have opened to assist learners in passing their qualification examinations. Moreover, some cases were reported in which MOOC learners were invited to learn in some institutes of higher education (e.g., Institute for Integrated Cell-Material Sciences, Kyoto University, 2014). It would be important to provide such career-enhancement programs, besides MOOC, for solving educational inequality.

There are some limitations in the present research. We analyzed the learners' data from just one institute (i.e., Kyoto University). As we confirmed the robustness of our results by analyzing the data of seven courses, we could not test whether these results depended on the MOOC providers. Meta-analytical procedures can integrate the results from different data sources, if the data have been opened. Future research can address these issues by cooperating with other MOOC institutes.

Another limitation is that, as the respondent ratio for all learners was low, the distribution of learners' motivations may be somewhat biased. However, it is difficult to assess all the learners' motivations because just a small number of learners were actively enrolled in course activities in most MOOC (Ho et al., 2014). A large proportion of MOOC learners, in most cases over 50%, simply enrolled in and have not accessed any contents in the courses. Moreover, a certain amount of the remaining learners just watch the course videos and do not respond to questionnaires or solve problems. Future research is needed to develop some procedures to assess the learning motivation of as many learners as possible.

5. Conclusion

Recently, some researchers have doubted whether MOOC can minimize social inequality (Emanuel, 2013), because most MOOC learners possess advantageous socioeconomic backgrounds (Hansen & Reich, 2015; Ho et al., 2014; Perna et al., 2014). By analyzing the data of MOOC learners in seven courses, we revealed that learners from disadvantageous socioeconomic backgrounds were highly motivated by extrinsic reasons. To realize one of the expected roles of MOOC, institutes need to keep providing career-enhancement programs besides the MOOC.

References

AbiGhannam, N., Kahlor, L. A., Dudo, A., Liang, M.-C., Rosenthal, S., & Banner, J. L. (2015). Experiences and motivations to attend an informal science lecture series. *International Journal of Science Education*, Part B, 6, 215-238.

Asano, S. (2002) Motivation that enhances lifelong learning: Open university students and regular university students. *The Japanese Journal of Educational Psychology*, 50, 141-151. (in Japanese with English abstract)

Barak, M., Watted, A., & Haick, H. (2016). Motivation to learn in massive open online courses: Examining aspects of language and social engagement. *Computers & Education*, 94, 49-60.

Emanuel, E. J. (2013). Online education: MOOCs taken by educated few. *Nature*, 503, 342.

Friedman, T. (2012) Come the revolution. *The New York Times*. Retrieved at 2016 December 4, from http://www.nytimes.com/2012/05/16/opinion/friedman-come-the-revolution.html

Gini, C. (1936). On the Measure of Concentration with Special Reference to Income and Statistics. *Colorado College Publication, General Series*, 208, 73-79.

Goto, T., Kudo, M., Mizumachi, E., & Kano, K. (2014). Verification on the utility of using the segmentation method developed in Australia to assess audiences of science and technology events. *Japanese Journal of Science Communication*, 15, 17-35. (in Japanese with English abstract)

Goto, T., Nakanishi, K., & Kano, K. (2018) A large-scale longitudinal survey of participation in scientific events with a focus on students' learning motivation for science: Antecedents and consequences. *Learning and Individual Differences*, 61, 181-187.

Hansen, J. D. & Reich, J. (2015). Democratizing education? Examining access and usage patterns in massive open online courses. *Science*, 350, 1245-1248.

Ho, A. D., Reich, J., Nesterko, S. O., Seaton, D. T., Mullaney, T., Waldo, J., & Chuang, I. (2014). *HarvardX and MITx: The first year of open online courses, fall 2012-summer 2013*. (*HarvardX and MITx Working Paper No. 1*). Retrieved at 2016 Febururary 1, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2381263

Institute for integrated cell-material sciences, Kyoto University (2014) *Kyodai, kaigai kara edX yushusei 6 mei wo shotai* [*Kyoto University has invited six foreign students with high achievement in "The Chemistry of Life."*] Retrieved 2017 December 4, from http://www.icems.kyoto-u.ac.jp/j/pr/2014/07/14-tp.html (in Japanese)

Kizilcec, R. F., & Schneider, E. (2015). Motivation as a lens to understand online learners: toward data-driven design with the OLEI scale. *ACM Transactions onComputer-Human Interactions*, 22.

Kovanović, V., Joksimović, S., Gašević, D., Siemens, G., & Hatala, M. (2015). What public media reveals about MOOCs: A systematic analysis of news reports. *British Journal of Educational Technology*, 46, 510-527.

Perna, L. W., Ruby, A., Boruch, R. F., Wang, N., Scull, J., Ahmad, S., & Evans, C. (2014). Moving through MOOCs: Understanding the progression of users in massive open online courses. *Educational Researcher*, 43, 421-432.

Rennie, L. J. (2007). Learning science outside of school. In S. K. Abell & N. G. Lederman (Eds.), *Handbook of research on science education* (pp. 125-167). Mahwah, NJ: Lawrence Erlbaum.

Ryan, R. M. & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55, 68-78.

Selwyn, N., Bulfin, S., & Pangrazio, L. (2015). Massive open online change? Exploring the discursive construction of the 'MOOC'in newspapers. *Higher Education Quarterly*, 69(2), 175-192.

Taguchi, M., Goto, T., Mohri, T., & Iiyoshi, T. (2017) Designing data analysis by integrating action logs in the MOOC and questionnaire surveys. *Kyoto University Researches in Higher Education*, 23, 109-118. (in Japanese with English abstract)

World Bank (2015) World development indicators [Database]. Retrieved at 2015 August 19, from http://data.worldbank.org/indicator/

Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2014). Understanding Student Motivation, Behaviors, and Perceptions in MOOCs. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 1882-1895.

(Received February 15, 2018; accepted April 2, 2018)