On The Tiny yet Real Happiness Phenomenon in The Mobile Games Market

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***Abstract*—This paper explores a counter-intuitive observation in the global mobile games market: that despite people in East Asian countries currently experiencing a challenging economic environment with lower disposable incomes and less leisure time than people in the West, they still spend much greater amounts of money on mobile gaming on a per-user basis. We link this situation to the tiny yet real happiness (TYRH) phenomenon [1]: a term coined by Haruki Murakami, frequently rumored as a future recipient of the Nobel Prize for Literature, in his 1986 book "*Afternoon at Langerhan's Island*". The TYRH phenomenon describes that, due to structural inequality problems, people (especially the members of younger generations) may lose their ambition to actively develop their careers, and instead to cherish small, ordinary moments of bliss. More concretely, people implicated in this phenomenon tend to maintain an attitude of "living in the moment" without regard for their current and future lives, and may even retreat into various non-career-related activities, including mobile gaming.**

In this paper, we investigate the possible role of the TYRH phenomenon in influencing how smartphone users spend money (and time) on mobile games. We find that countries with long work hours, higher scores on the Gini index, lower unemployment rates, and lower life satisfaction are all associated with higher per-user spending on mobile games on both the App Store and Google Play platforms. This suggests that the TYRH phenomenon is indeed positively associated with mobile game-playing and spending behavior, and that countries where the phenomenon is more prominent are likely to contribute disproportionately to the mobile games market, now and in the future.

***Keywords*-Game Analytics, Mobile Games, World Values Survey**

I. Introduction

During the past decade, the tiny yet real happiness (TYRH) phenomenon [1] has come to be regarded as prevalent in some Asian countries, including China, Hong Kong, Japan, Singapore, South Korea, and Taiwan. It refers to younger people chasing small, disconnected moments of bliss rather than actively engaging with or developing their careers, partly because they are now are facing unfriendly working environments, unbalanced salary structures, and high living levels of stress [2]. In other words, under the prevalent tough economic conditions, which are seen as structural and rigid, hard work does not necessarily lead to better material or personal rewards; consequently, many young people lose the will to fight their way up the career ladder and rather cherish small, ordinary moments in bliss [3].

At the same time, while smartphones and mobile games on the top of them have been more popular than ever before, a major trend is that mobile games are now designed to be easily "fragmentized" in order to fit into the daily lives of modern people [4]. Such games reach out not only to the same people who play games on PCs and consoles but to those who have not played any computer games before. According to [5], the global mobile games market was worth US $30.4 billion in 2015 and is expected to grow to US $52.5 billion in 2019.

In this paper, we investigate whether the TYRH phenomenon plays an important role in influencing how smartphone users spend money (and time) on mobile games. Our hypothesis is that smartphone users in those countries where the TYRH phenomenon is prominent will be more engaged with mobile games, for the following reasons:

1) Unfriendly working environments usually involve long work hours, short vacation days and high levels of work-related stress [6].
2) People experiencing high levels of work-related stress and/or who have little or no vacation time tend to enjoy short joy during whatever leisure time they have, rather than going for longer one, such as traveling long distances, due to the lack of sufficient time.
3) Low disposable income prevents people from purchasing pricy items such as luxuries, cars or houses, but does not completely forestall minor expenditures that bring immediate positive feedbacks.
4) Nowadays, a major trend that mobile games are designed to be "fragmentized" [7] and low spending threshold [8] perfectly fits into the daily lives of modern people who are experiencing unfriendly working environments and low disposable income.

Simply put, in countries where the TYRH phenomenon is more prominent, a higher proportion of people do not have access to traditional vacations and luxury spending; instead, their fragmented leisure time and low disposable incomes lead them to seek small, affordable "escape" experiences, including especially mobile games. These games can be of very short duration and/or can readily be paused and resumed by the user, and thus can easily fit into fragmented schedules, while in-app purchases (IAP) normally involve transactions of a few dollars or less, and can provide an immediate, perhaps fleeting, sense of happiness and achievement. For the above reasons, *we conjecture that mobile-game use will be especially noticeable in countries where the TYRH phenomenon is prevalent, and consequently that those countries' gross revenue contributions to the mobile games market will be higher than the contributions of countries where the TYRH phenomenon is less* *prevalent*.

Our data sources can be divided into two categories: mobile games market statistics, and measures related to the TYRH phenomenon. For the first category, we use the App Annie database[1], which is used by more than 94% of the top 100 mobile app developers to analyze their competitors [9], to obtain the country-by-country gross revenues of each of our two targeted mobile gaming platforms (i.e., App Store and Google Play). For the second category, there were no pre-existing concrete methods for quantifying the TYRH phenomenon, so we have developed a method of our own based on a wide range of socio-economic indicators that indirectly represent the effect of the TYRH phenomenon on the mobile games market. Specifically, we collected numerous country-level characteristics from the Organisation for Economic Co-operation and Development (OECD), the World Bank, Google Public Data [10], and World Values Survey (WVS) [11] covering the investigated countries' economies, working conditions, socio-demographics, cultural indices and state of technology development. Because the various datasets we utilized did not all cover the same group of countries, our aggregated dataset included only 42 countries; however, these countries collectively contributed 90.3% of the total revenue on the App Store and Google Play platforms. Further details regarding our data sources and aggregation procedures are provided in Section III.

We developed two statistical models to investigate the relationships between the country-level characteristics of the 42 countries and their contributions to the gross revenues of mobile gaming platforms.

Model 1: User Contribution Model. The User Contribution Model is intended to describe the general trends in average user contributions to the revenue of mobile game platforms based on country-level factors, such as wages, work hours, education levels, and life satisfaction. We find that the User Contribution Model generally works well (with an adjusted $R^2 > 0.8$); however, as we expected, the contributions of certain East Asian countries cannot be accurately predicted using this general model, where such countries are known to have tougher living and working conditions (especially for younger generations), as shown in Figure 6.

Model 2: Contribution Deviation Model. The Contribution Deviation Model is intended to describe and explain why certain countries' actual per-user contributions to the mobile games market cannot be accurately predicted by the User Contribution Model. As these same countries are strongly associated with the TYRH phenomenon, we use the Contribution Deviation Model to confirm the effect of the TYRH phenomenon on the mobile games market as well as to explain how the TYRH phenomenon can be observed by using socio-economic, developmental, and cultural factors.

The contributions made by this paper are three-fold:

1) As far as we know, this is the first paper investigating and linking the TYRH phenomenon to mobile games usage and the revenue generated by the mobile games market.
2) This research confirms that higher levels of economic development and education are associated with increased user spending on mobile games, as one might reasonably expect. Interestingly, however, while high levels of life satisfaction are associated with increases in spending on mobile games, low life satisfaction is also associated with increases in such spending. This serves as preliminary evidence that people in tough living and working environments are likely to seek entertainment from mobile games.
3) Lastly, this paper confirms that countries with long work hours, higher scores on the Gini index, lower unemployment rates, and lower life satisfaction are associated with higher per-user spending on mobile games on both the App Store and Google Play platforms. This indicates that the TYRH phenomenon is indeed positively associated with mobile game play and spending behavior, to such an extent that countries where the TYRH phenomenon is most prominent contribute more to the mobile games market than other countries do. This markedly higher spending on games among people with less money and less leisure time is intuitively surprising, yet in keeping with our second major finding above.

[1] App Annie, https://www.appannie.com/

The remainder of this paper is organized as follows. Section II contains a review of the relevant prior literature. We elaborate our data sources and how they have been aggregated into a working dataset in Section III-C. In Section IV, we present the User Contribution Model, which describes the general relationship between countries' socio-economic conditions and their contributions to mobile games markets. We then present the Contribution Deviation Model, which explains the former model's prediction deviations in Section V. Finally, in Section VI, we present our conclusions and several potential directions for future research.

II. Related Work

To the best of our knowledge, this is the first academic study of the TYRH phenomenon. We can only find TYRH reports in literary and news sources and a TYRH-similar study [12] of the lottery purchasing in the US. We also find a study about how cultural differences effect East-Asian people on playing social network games [13]. In addition, since we try to prove the TYRH phenomenon by analyzing the between-country differences of players' mobile-gaming behavior, we also find the previous academic studies relevant to our study in three categories: (1) mobile commerce (m-commerce) prediction, (2) the freemium business model (i.e., free-to-play plus premium), and (3) fragmentized design.

The term, tiny yet real happiness, was originated by Haruki Murakami in his book "*Afternoon at Langerhan's Island*" [1]. It is used to describe the small, transient moments of bliss [3] felt during mundane activities like eating freshly baked bread, falling asleep beside one's cat, and reading a magazine in solitude while waiting for one's food to arrive at a restaurant [14]. However, this phenomenon has also been used negatively, to describe people (especially the young) who have lost or are in danger of losing their career ambitions due to their focus on disconnected, economically irrelevant blissful moments. In Taiwan, where the labor market is characterized by long work hours, low pay, and informal working arrangements, the Premier once said that Taiwanese would enjoy "a little happiness in hand" if the number of public holidays were to increase [14]. At its worst, according to [3], the TYRH phenomenon is a form of escapism and an excuse for complacency and apathy in response to the strains exerted by modern life. In [12], the authors analyzed the purchasing behavior of lotteries, which we found similar to the TYRH phenomenon, proving that the poor consider lotteries as an effective financial investment, rather than as an entertainment.

In [13], the authors proved that the culture of vertical collectivism (VC) could indirectly predict spending on virtual goods and the East-Asian countries have been categorized as more vertical collectivism. This result may imply why the East-Asian countries such as Japan, Korea and Taiwan [**?**] are more willing to spend on free-to-play business model.

Prediction and explanation modeling of consumers' mobile-games spending is a popular topic, but only a few studies have engaged in country-level analysis. Alain et al. [15] focused on explanations of consumers' adoption of m-commerce in two developing countries, Malaysia and China, and found that Malaysian people—whose educational levels are lower—tend to use m-commerce for entertainment activities such as downloading games, music and ring tones. Given that the correlation between educational levels and age is significantly negative in Malaysia, one explanation could be that older Malaysian users have more spending power. Hanting Xie et al. [16] built a prediction model of better generality with event-frequency to predict players' first purchases; where Rafet Sifa et al. [17] tried to predict if a purchase would occur and, if it did, how many further purchases would occur due to player in-game behaviors. Overall, these studies did not systematically link in-game data to cross-country analysis.

The freemium business model has emerged as a key trend adopted by mainstream mobile games to reach the largest possible audience. Seufert et al. [18] defines that the freemium business model stipulates that a product's basic functionality is free, but advanced functionality or premium access are fee-based. He also identifies Candy Crush Saga as an iconic game of the mobile era, proving that games can generate great revenue if they have a large user base and good in-app purchase design. Park and Lee [19] modified the theory of consumption values to investigate online game users' perceived value of purchasable game items and found that the enjoyment, character competency, visual authority, and monetary values are appropriate for describing the perceived value of game items. This helps explain the success of the freemium model. Meanwhile, Dimitar [20] includes freemium design and monetization of mobile games as part of a framework of best practices and in-depth game design schematics for developers to follow. Mobile games such as Clash of Clans in the West and Puzzle & Dragon in the East have followed this model and found considerable success.

Nanda Kumar [8] has pointed out that, when combined with a personalized pricing strategy, the freemium model is able to maximize revenue by reaching massive numbers of people.

TABLE I
APP ANNIE DATA SUMMARY

	Gross Revenue (USD)	
Period	App Store	Google Play
Jan 2011–Dec 2011	$2,189,116,990	N/A
Jan 2012–Dec 2012	$4,622,863,527	$520,149,429
Jan 2013–Dec 2013	$10,903,498,760	$2,884,007,087
Jan 2014–Aug 2014	$12,018,988,022	$4,063,283,367

Eui Jun Jeong et al. [21] investigated how the characteristics of mobile games differ from other platforms such as consoles, PCs, and arcade games, and summarized these differences as portability, accessibility, networkability and simplicity. These characteristics attract a broader range of users and enable them to play in a shorter amount of time. According to [22], more and more consumers decide to use their fragmentary free time to use mobile apps. Though we were only able to identify one Chinese report on the "fragmentized" design (i.e., short playing time per game turn) of mobile games [7], it can easily be observed that almost all of the popular freemium games, including but not limited to Angry Birds, Candy Crush, Clash of Clans, and Hearthstone, have short-playing-time designs, as compared to games designed for other types of platforms.

III. Data Description

In this section, we describe the App Annie dataset, the country-characteristics dataset, and present a preliminary analysis of the TYRH phenomenon. Briefly, for the App Annie dataset, we collected mobile-gaming gross-revenue data from 153 countries on App Store and from 49 countries on Google Play. In country-characteristics dataset, we collected comprehensive country-level datasets to capture a range of countries' characteristics in terms of general economic conditions, working conditions, socio-demographics, cultural indices and technological development. In regard to data aggregation and cleaning, we created a full dataset of 42 countries without World Values Survey (WVS) data for the User Contribution Model, and a reduced dataset of 32 countries with WVS data for the Contribution Deviation Model, in Section IV and V, respectively. Lastly, our preliminary analysis investigated the relationship between average user contributions and certain country characteristics, and identified an intriguing phenomenon: that the average user contribution has a positive correlation with work hours per week, and a negative correlation with the unemployment rates.

A. App Annie Dataset

App Annie[1] is the most popular platform for mobile app analytics and app market data, used by 94% of the top 100 app developers when analyzing trends in the app market [9]. It offers comprehensive country-by-country data on the app gross revenues of both App Store and Google Play, as well as the exact daily revenues of each app developer. It covers 76 categories of app, including games. Table I sets forth the total gross revenue from the mobile games category on App Store and Google Play from 2011 to 2014.

TABLE II
42 COUNTRIES AND ALL INDICATORS

Category	Indices
Economic and Working Condition Indices	gross domestic product (GDP) [23], export rate [24], Gini index [23], unemployment rate [25], minimum wage per hour [26], disposable salary after tax [24], paid vacation days [26], paid public holidays [26], work hours per week [27]
Socio-demographics and Cultural Indices	work attitude [11], life and work habit [11], sense of self [11], world religion dataset [28], human development index (HDI) [29], education index [29], life expectancy [30], satisfaction index [30], happiness index [30], death rate [31], median age [31], population [32]
Technology Indices	Internet development index [33], Internet penetration rate [24], smartphone usage rate [34], smartphone operation system market share [35]
Continent	**Country list**
Asia	Hong Kong (HK), India (IN), Indonesia (ID), Israel (IL), Japan (JP), South Korea (KR), Malaysia (MY), Philippines (PH), Russian Federation (RU), Singapore (SG), Taiwan (TW), Thailand (TH), Viet Nam (VN)
Africa	Egypt (EG), South Africa (ZA)
Europe	Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Finland (FI), France (FR), Germany (DE), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Spain (ES), Sweden (SE), Switzerland (CH), Turkey (TR), Ukraine (UA), United Kingdom (GB)
Oceania & United States	Australia (AU), New Zealand (NZ), United States (US)
South America	Argentina (AR), Brazil (BR), Mexico (MX)

B. Country Characteristics Dataset

We built the country-characteristics dataset by collecting data from three main categories: economic and working-condition indices, socio-demographics and cultural indices, and technology indices. The resulting data matrix contained 250 rows of unique countries and 229 columns of country characteristics. The upper part of Table II shows the detailed indices that we found to be important during our experiments.

1) Economic and Working Conditions Indices: The economic indices mainly focus on broad nation-level or between-country differences: for instance, in overall economic structure and development, income distribution, and export performance. The working-condition indices are also at the nation level, but are focused specifically on labor-related issues such as individual purchasing power and amount of leisure time. Together, these indices enable us to compare the overall material conditions of life across multiple countries.

2) Socio-demographics and Cultural Indices: Our socio-demographic data can be divided into two categories: (1) people's mental and physical health levels, and (2) population sizes and religious composition. Cultural indices, on the other hand, reflect: (1) people's values and beliefs regarding life, money and leisure time; (2) their attitudes toward competition, hard work and success; and (3) whether their tasks are manual or intellectual, routine or creative, and dependent or independent. These cultural indices were derived from the dataset of the World Values Survey [11], a global research project that explores not only people's values and beliefs but also their attitudes toward their lives, careers, environments, subjective well-being, and so forth. We collected these diverse types of cultural data in order to flesh out areas of life that general economic data cannot reveal.

3) Technology Indices: Mobile gaming is a recent development, and requires relatively strong technology infrastructure, such as wired and wireless network coverage. We hence collect technology datasets relating not only to how accepting of technology various countries are, but also what level of Internet technology they currently possess.

A major challenge of country-characteristic collection was finding datasets that matched as many of the countries in the App Annie dataset as possible.

C. Data Aggregation

As previously mentioned, we created a 42-country dataset for the User Contribution Model described in Section IV, and a 32-country dataset for the Contribution Deviation Model described in Section V. Both of these datasets included both App Annie data, and the smaller of the two also contained country-characteristics data from WVS. The WVS dataset was additionally included in the smaller one to capture the between-country cultural differences but the trade-off is the reduction in the number of countries, which will be further explained in Section V.

With regard to the period to be studied, we selected country-by-country gross revenues for both platforms from September 2013 to August 2014. This was because, prior to September 2013, Google Play served only 10 countries, rendering data from any earlier period inadequate for large-scale cross-country analysis. The number of countries covering complete App Annie and country-characteristic data over the selected time period is 42. The 32-country dataset was later created by aggregating 42-country dataset and WVS data. In both datasets, China was excluded, despite being important in App Store terms, because it does not allow Google Play to operate on its territory; and this is also a reason for the larger drop in the App Store's total gross revenue after data aggregation, as compared to Google Play's, since China contributes up to 10% of the App Store' total revenue. As the result, our 42-country dataset contained 83 variables (without WVS data), and our 32-country dataset contained 98 variables (including WVS data). The lower part of Table II shows the 42-country list, and Table III presents the aggregated revenue of the App Store and Google Play.

TABLE III
AGGREGATED DATASETS

	App Store revenue ($1M)	%	Google Play revenue ($1M)	%
32 countries	$6,429	78%	$5,142	97%
42 countries	$6,844	83%	$5,335	98%
total revenue	$8,196	100%	$5,280	100%

D. Preliminary Analysis

The observed variables for our preliminary analysis were average user contributions (AUCs) on App Store and Google Play. AUC is defined as the average revenue per iOS / Android user on App Store / Google Play by

$$\begin{aligned}\text{total users}_{i,j} = &\ \text{population}_j \times \\ &\ \text{smartphone usage rate}_j \times \\ &\ \text{market share}_{i,j}\end{aligned} \tag{1}$$

$$\text{AUC}_{i,j} = \frac{\text{gross revenue}_{i,j}}{\text{total users}_{i,j}}, \tag{2}$$

where the subscript i stands for the platforms, ap stands for the App Store, gp for Google Play, and j for each of 42 countries: AR, AU, ..., ZA.

We used AUCs as the response variable and all the other variables as the predictors to observe the country differences between mobile-gaming spending and other country characteristics. Figure 1(a) and Figure 1(b) set forth the AUCs of App Store and Google Play and the nation-level work hours per week. It is clear that Asian countries in the sample were characterized by longer work hours than the Western countries, though this did not appear to negatively impact the AUCs of the Asian countries, considered as a group. On the other hand, Figure 2(a) and Figure 2(b), which show AUCs vis-a-vis unemployment rates among users of both platforms, reveal an interesting negative relationship between unemployment and AUCs in all 42 countries. These two findings serve as important clues regarding the TYRH phenomenon.

IV. USER CONTRIBUTION MODEL

We built the User Contribution Model using multiple linear regression to answer the question, What country-level characteristics cause its AUC to differ from the AUCs of other countries? We defined the response variable as the total AUCs on both platforms by country, and used the larger 42-country dataset for variable selection.

Figure 3 shows the AUCs on App Store and on Google Play, and indicates that iOS users generally spend more, and have a smaller spending variance, than Android users do. This reveals quite different market characteristics: given the iPhone's high price [36], there is a fairly high threshold for users to obtain one. On the other hand, the Android smartphone provides options for people at a wide range of economic levels. In other words, the typical iOS user is inherently more likely to be able to have a high and steady level of participation in the mobile games market, regardless of whether he/she lives in a country with good or poor general economic conditions; whereas Android users' AUCs are low in poor countries and high in rich ones countries. We can also see that South Korea was the only country where Android users spent much more than iOS users did during the studied period. This may be because South Korea is the headquarters of two smartphone manufacturers, Samsung and LG Electronics.

TABLE IV
PRELIMINARY USER CONTRIBUTION MODEL

User Contribution Model			
Variable	β	*p-value*	*VIF*
wages per hour (log)	0.740	0.000 ***	4.45
satisfcation index	-0.303	0.003 **	1.99
education index	0.432	0.000 ***	3.18
Gini index	0.288	0.000 ***	1.29
unemployment rate (log)	-0.377	0.000 ***	1.08
$adj\text{-}R^2$: 0.819			

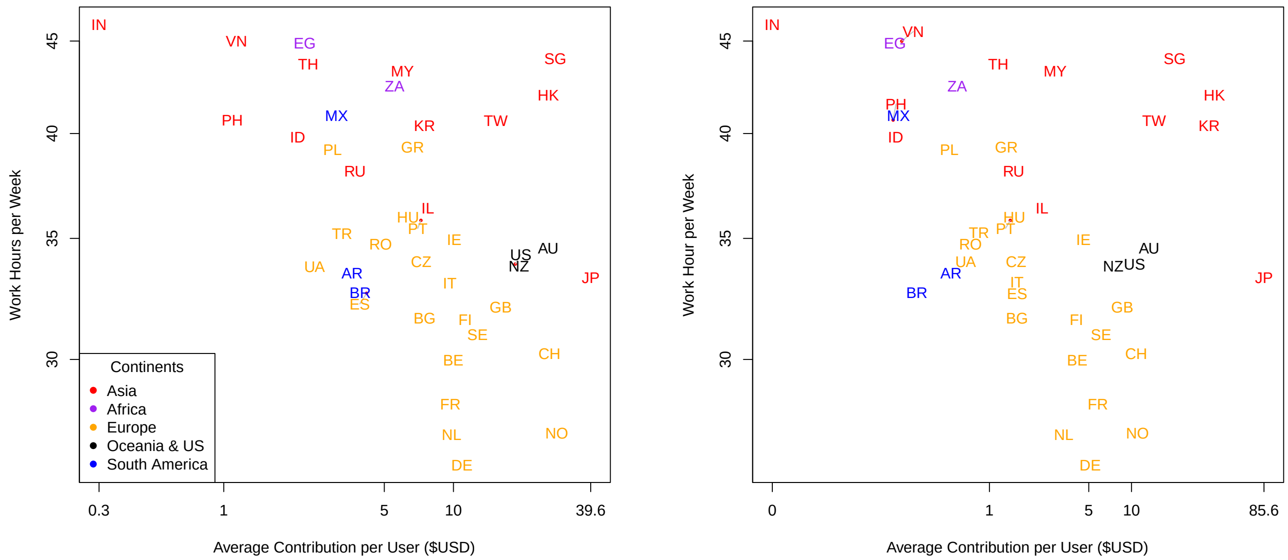
We developed a semi-automatic methodology for variable selection. It is structured by: (1) identifying possible response variables for the question, (2) selecting reasonable datasets, (3) checking the scatter plots of each explanatory variable and response variable to understand their relationship for data transformation, (4) measuring the variance inflation factor (VIF) between variables and removing the explanatory variables whose VIF > 10, (5) running stepwise regression with bidirectional elimination for model selection, (6) rechecking the variables' relationship and importance and removing the least important one, and reiterating (1) to (6) until the model selection ends up with the most significant explanatory variables, the least multi-collinearity and the largest adjusted R^2.

After we put all country-characteristics datasets through our variable-selection process, the explanatory variables that emerged were satisfaction index, education index, Gini index, wages per hour (log) and unemployment rate (log). However, from Table IV, we can see that the satisfaction index's coefficient flips from positive to negative despite the max VIF for these variables being less than 5. Principal component analysis (PCA) was applied to address this interaction problem and to gain a clearer understanding of the reason for the flipped sign. We standardized both satisfaction index and wages per hour (log) to z-score to eliminate their scaling difference, and then rotated their co-ordinate axes to remove their correlation. Based on this rotation matrix, the PC1 was defined as "having a High Wage And Satisfied" (HWAS), and the PC2 as "having a High Wage But Unsatisfied" (HWBU).

Rotation:

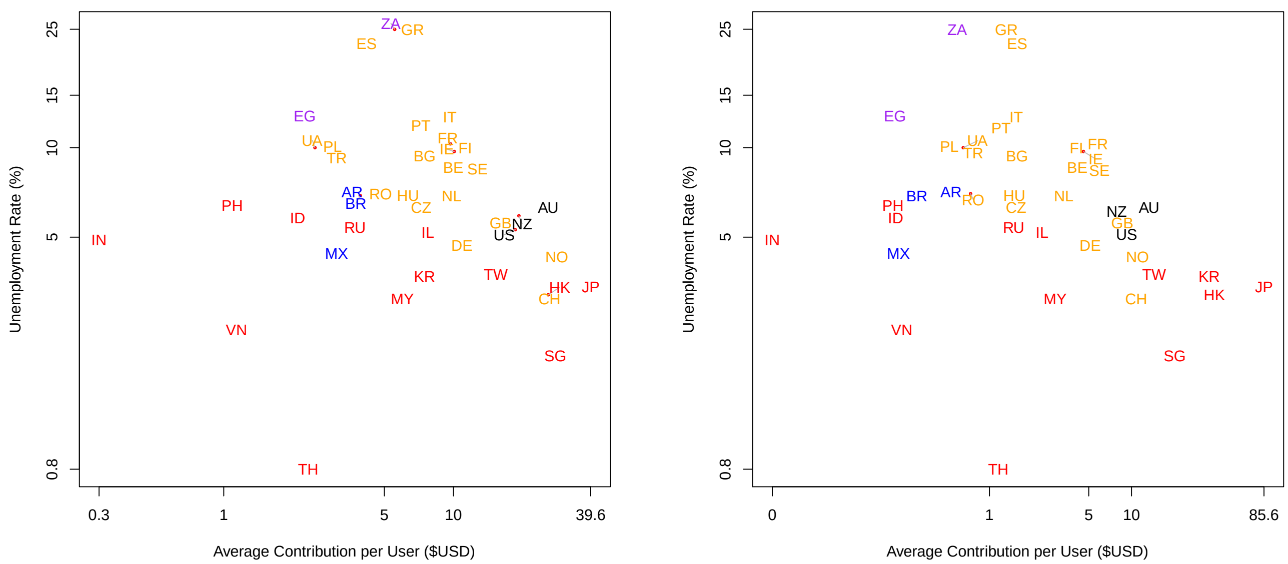
	PC1	PC2
satisfaction index	0.7071068	-0.7071068
wages per hour (log)	0.7071068	0.7071068

Next, we performed K-means clustering to identify group differences among countries based on all six standardized variables of the User Contribution Model. The distance function was root mean square error (RMSE). Four clusters were found to provides a sufficiently clear separation of countries, as shown in Figure 4. We performed dimensionality reduction from the six variables involved in the model to three new components using PCA. In Figure 4, the numbers below the country names represent the third component. We divided the



(a) App Store (b) Google Play

Fig. 1. Average User Contribution with Work Hours per Week



(a) App Store (b) Google Play

Fig. 2. Average User Contribution with Unemployment Rate

42 countries into four groups. The "diligent" group (shown in red) are Japan (JP), Hong Kong (HK), South Korea (KR), Singapore (SG) and Taiwan (TW), all of whose third components were markedly lower than the countries in the "developed" group, which contains Northern and Western European countries, plus the US and Australia (AU). The "walfare" group (blue) contains the Middle and Eastern European countries and Russia (RU); and the "developing" group (black), the Southeast Asian and South American countries.

From the final User Contribution Model (Table V), we can

TABLE V
FINAL USER CONTRIBUTION MODEL

Variable	β	*p-value*		*VIF*
HWAS	0.393	0.000	***	2.52
HWBU	0.455	0.000	***	1.86
education index	0.474	0.000	***	3.18
Gini index	0.288	0.000	***	1.29
unemployment rate (log)	-0.377	0.000	***	1.08
$adj\text{-}R^2$: 0.819				

(Table heading spanning all columns: *User Contribution Model*)

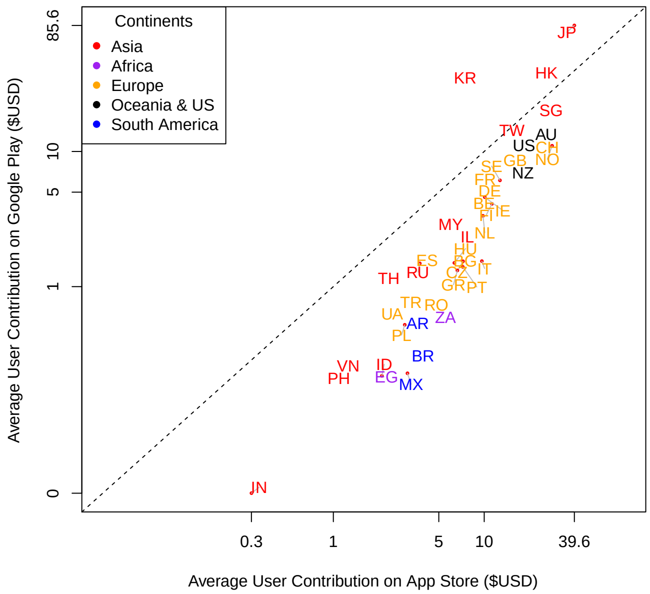


Fig. 3. AUC Difference of 42 Countries on App Store and Google Play

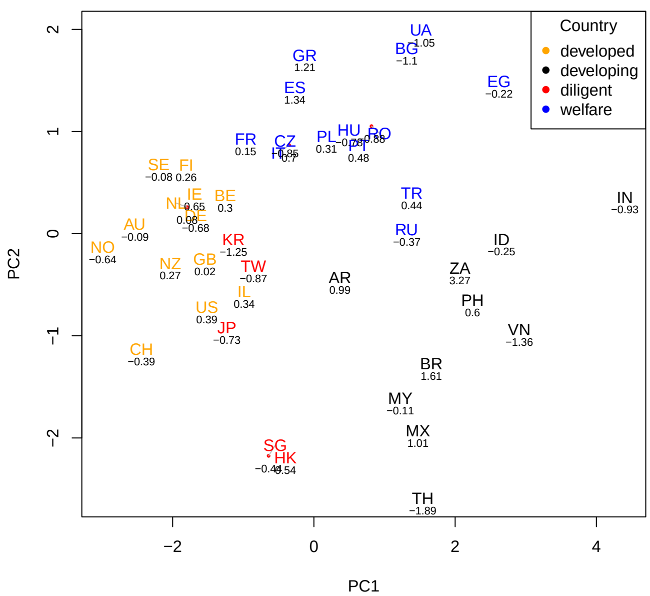


Fig. 4. K-means Clustering Result of 42 Countries

clearly see that countries AUCs had strong relationships with the selected country indices. Overall, higher levels of economic development and education in a country are associated with higher levels of users' spending on mobile games there. It seems intuitively correct that a better overall economic situation will afford users more money and time to spend on entertainment, especially given that mobile games are designed with low spending thresholds but high effects. Additionally, higher levels of education tend to instill people with a sense of the importance of entertainment, and this leads them to invest in it more. It is perhaps more interesting that, under adequate economic conditions, high life satisfaction was associated with high user contribution spending on mobile games, but low life satisfaction had an even stronger positive association with such spending ($\beta_{HWBU} > \beta_{HWAS}$). Unfriendly social structures and difficult working environments also appear to push users to spend more on mobile games. In other words, people in places with higher scores on the Gini index may be more likely to pursue small, transient feelings of bliss rather than dreaming big, insofar as M-shaped societies lead to lower society mobility. Lower unemployment rates association with higher AUCs, meanwhile, may be due to short and fragmented spare time on the part of a hardworking population. All of the factors mentioned in this paragraph serve as preliminary evidence for the TYRH phenomenon, and hints as to how to dig further into it.

A more detailed look at Figure 5 provides a more complete understanding of what country-level characteristics impact on a given country's contribution to the international mobile-gaming market; and this in turn led us to build the Contribution Deviation Model, to further understand the TYRH phenomenon in the "diligent" group of countries. The main differences between the diligent and developed countries are their Gini index scores and their unemployment rates. Both of these groups contribute disproportionately to mobile-gaming revenues because of their high levels of education and economic development. It would seem that the lower levels of life-satisfaction, higher Gini scores, and lower unemployment rates of the diligent countries to some degree urge their people to live more in the moment. On the other hand, although the welfare countries and diligent ones have similar levels of education, economic development, and life satisfaction, the lower Gini scores and higher unemployment rates of the welfare group suggest that their people are allowed more opportunities, choices and spare time in life. Despite the developing countries generally having lower levels of education and economic development, making them less able to afford high spending on mobile games, one of these countries, Malaysia (MY), exhibits similar trends to the diligent group with regard to its mobile-game spending. Malaysia has a high Gini score and a low unemployment rate, factors that (as we have seen) are strongly associated with higher user contributions, but its lower level of education and economic development would tend to hamper its user contributions, making its mobile-gaming spending not as large as the diligent group's. On the whole, however, its current overall conditions and user contributions demonstrate excellent potential for mobile-game market expansion.

V. Contribution Deviation Model

We built the Contribution Deviation Model to help us determine why the diligent countries contributed so disproportionately to the revenue of the mobile-gaming market, as compared to other countries and groups of countries. The developed group, despite having the best economic development with average wages of US$14.70 per hour, have AUCs of US$11.60 per user on average. However, while the diligent have average wages of just US$5.00 per hour, their AUCs reach an average of US$30.40 per user, i.e., US$55.50 of in Japan, US$31.70

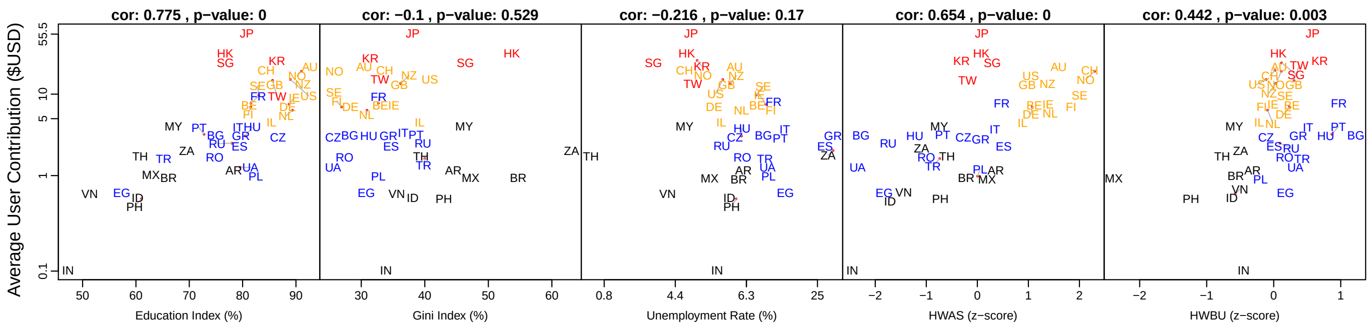


Fig. 5. AUC vs. 6 Selected Variables in User Contribution Model

in of Hong Kong, US$25.90 of in Korea, US$24.20 of in Singapore, and US$14.80 of in Taiwan.

To answer the question of why these Asian countries spent so much on mobile games in both relative and absolute terms, we first built two simple linear regressions for the prediction of AUCs in the Android and iOS markets to more precisely capture these two markets' differences. Wages per hour was selected as the predictor variable, as it had the strongest total effect in the User Contribution Model. As well as the diligent contributing markedly more than they are predicted to do, Figure 6 indicates that Malaysia also contributed to this market beyond expectation. This corresponds to the conclusions of our User Contribution Model analysis.

Next, we built the Contribution Deviation Model using multiple linear regression. The new response variable is country-level contribution deviation, i.e., a given country's actual AUC divided by its predicted AUC. For the selection of explanatory variables, we used the smaller, 32-country dataset, including the answers to 15 selected questions from the WVS to more accurately capture the differences in cultural perspectives among countries. However, as we mentioned in Section III-A, 10 countries, which are BG, CZ, EG, GR, IN, IE, IL, PT, RO and VN, are not present in the WVS dataset, we hence removed them out. The 32 countries in this dataset preserved 78.3% of total revenue on App Store, and 96.4% of total revenue on Google Play in App Annie dataset. The contribution deviation formula can be described as follows:

$$\text{contribution deviation} = \frac{y_{ap} + y_{gp}}{\hat{y}_{ap} + \hat{y}_{gp}}, \tag{3}$$

where the subscript ap stands for the App Store and gp stands for Google Play. The previously described methodology for the selection of variables was used again in this case, and the explanatory variables that we eventually arrived at were Gini score, smartphone usage rate, work hours, disposable salary (log), unemployment rate (log), and the survey answers to two Likert-scale WVS questions, wvs.023 and wvs.099.

$wvs.023$:

All things considered, how satisfied are you with your life as a whole these days? 1 means you are "completely dissatisfied" and 10 means you are "completely satisfied" where would you put your satisfaction with your life as a whole?

$wvs.099$:

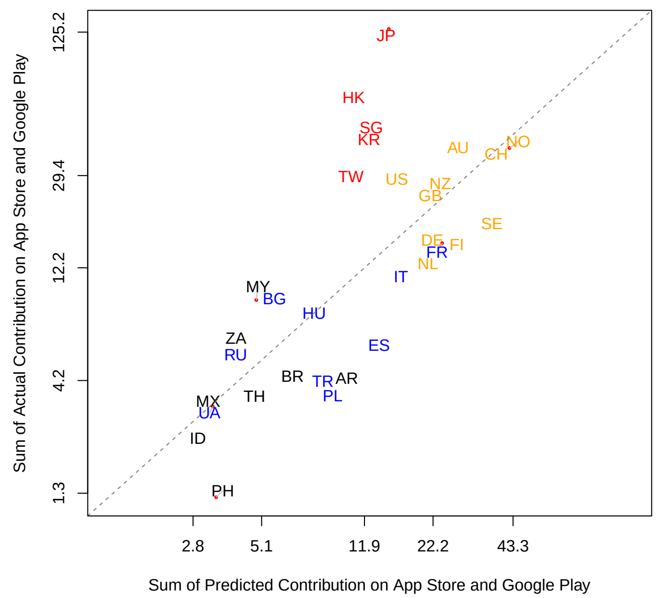


Fig. 6. Contribution Deviation of 32 Countries

Statement one: competition is good. It stimulates people to work hard and develop new ideas; statement two: competition is harmful. It brings out the worst in people. 1 means you agree completely with the statement one; 10 means with the statement two.

The question, wvs.023, outweighed and therefore replaced the original satisfaction index during VIF screening-out. The correlation between wvs.023 and satisfaction index reached 0.921. We also found that the smartphone usage rate again exhibited a sign-flip. The smartphone usage rate had a 0.73 correlation with disposable salary (log) despite low VIF values. We applied PCA, and found that the flipped sign was mainly caused by the relatively low smartphone usage rate in Japan. Based on the rotation matrix, the PC1 was defined as "having High disposable Salary and High Smartphone usage rate" (HSHS), and the PC2 as "having High disposable Salary but Low Smartphone usage rate" (HSLS).

The wvs.023 outweighs and replaces the original satisfaction index during VIF screening-out. Their correlation reaches 0.921. We also find that the smartphone usage rate shows

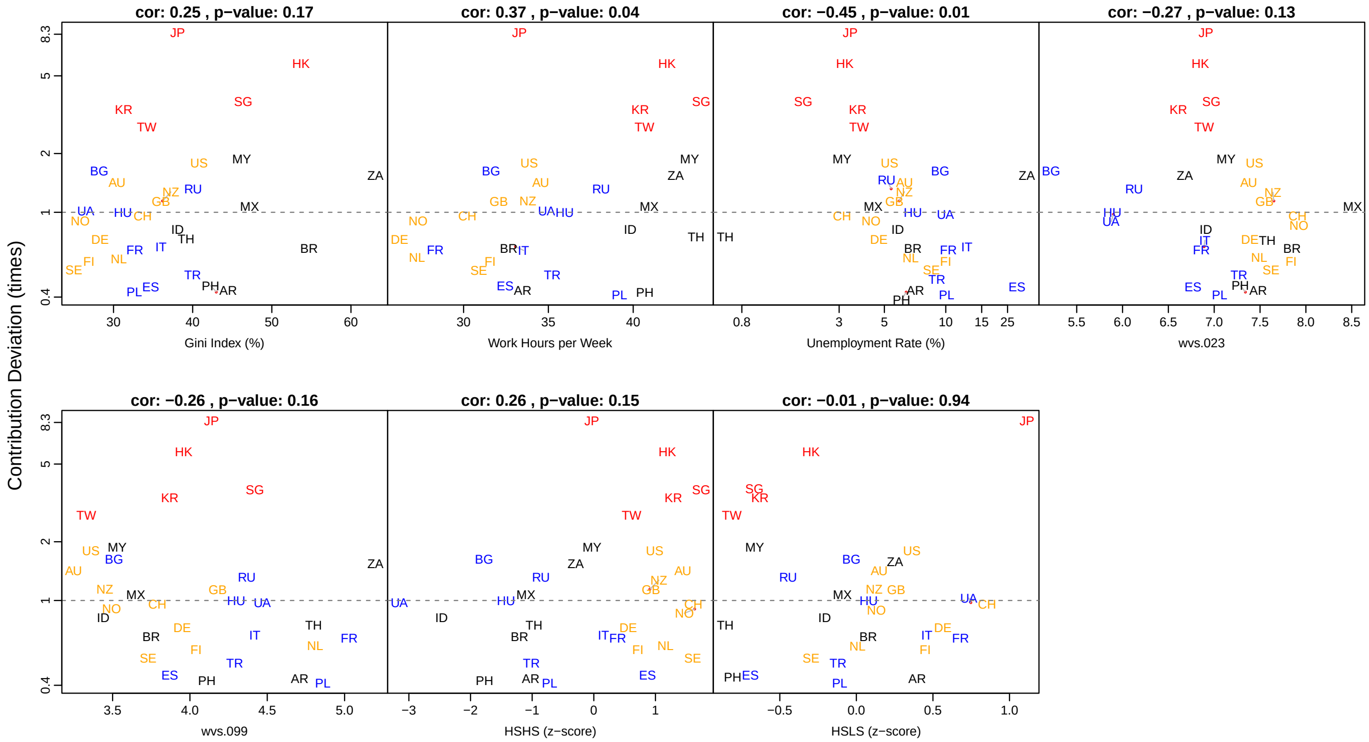


Fig. 7. Contribution Deviation vs. 7 Selected Variables in Contribution Deviation Model

TABLE VI
DEVIATION MODEL SUMMARY

	Contribution Deviation Model		
Variable	*β weight*	*p-value*	*VIF*
Gini index	0.307	0.011 *	1.99
work hours	0.461	0.006 **	3.68
unemployment rate (log)	-0.434	0.000 ***	1.47
wvs.023	-0.671	0.000 ***	1.49
wvs.099	-0.352	0.000 ***	1.17
HSHS	0.548	0.000 ***	1.37
HSLS	0.563	0.000 ***	1.97
$adj\text{-}R^2$: 0.806			

the sign flip again. The smartphone usage rate has a 0.73 correlation with disposable salary (log) despite of low VIF values. We apply PCA and find that the flipped sign is mainly caused by the relatively low smartphone usage rate at Japan in the diligent group. Based on the rotation matrix, the PC1 is defined as "having High disposable Salary and High Smartphone usage rate" (HSHS); the PC2 is as "having High disposable Salary but Low Smartphone usage rate" (HSLS).

Rotation:

	PC1	PC2
smartphone usage rate	0.7071068	-0.7071068
disposable salary (log)	0.7071068	0.7071068

Based on the data shown in Table VI, we can confirm that: (1) Unfriendly social structures and bad working conditions are strongly associated with the TYRH phenomenon: i.e., a high score on the Gini index and a low unemployment rate predict the greater contribution deviation, and when the variable of work hours is added into the model, it can be seen that longer hours stimulate people to spend more, perhaps because mobile gaming can be fit into time-fragmented daily routines. (2) High disposable salary and high smartphone usage rates are associated with greater contribution deviation, with Japan being the only country showing exhibiting relatively low smartphone usage despite high disposable salary. And (3) low life satisfaction is associated with greater contribution deviation, as mentioned in the conclusion of Section IV, as is a positive attitude toward competition (as measured by a low level of agreement with wvs.099).

A detailed examination of Figure 7 gives us a better understanding of the likely influence of the TYRH phenomenon on the mobile-games market. Our preliminary evidence indicates that the TYRH phenomenon occurs most strongly in countries with high Gini scores, low unemployment, and low life satisfaction, and in our Contribution Deviation Model, these factors became more significant, with the countries' contribution deviations demonstrating strong relationships with the three above-mentioned variables and with longer work hours. This is not to say that the TYRH phenomenon only occurs in the diligent countries, but rather that it is the most serious there. In addition, in the developed and diligent countries, generally good economic conditions (as measured by disposable salary) and high states of technological development (as measured by smartphone usage rates) do not hinder contribution deviation, whereas, in developing countries, poor economic conditions and technological development do hinder it.

It is interesting that attitudes toward competition seemed to have a differential impact for different groups of countries. Specifically, the developed, developing and welfare groups' positive attitudes to competition may have tended to increase their contribution deviations because their living conditions are less rigorous: with low Gini scores, short work hours and high unemployment rates. Tn the diligent countries, in contrast, reported broadly negative attitudes toward competition (as measured by high levels of agreement with wvs.099 score). We speculate that the people of the diligent countries fear competition because their economic environments are already too harsh. This negative attitude toward competition may also correspond to the lack ambition of among the younger generation that the TYRH phenomenon embodies.

In conclusion, our Contribution Deviation Model appears to confirm the existence of the TYRH phenomenon in the five diligent countries, which are characterized by exceptionally high contribution deviations as well as higher Gini scores, longer work hours, lower unemployment rates, lower life satisfaction, and lower disposable salary than the developed countries in our sample. These difficult living conditions may be the root cause of the TYRH phenomenon in the diligent countries, at least insofar as such conditions would tend to render their populations less ambitious. The diligent group's negative attitudes toward competition also correspond to the life attitudes described by the TYRH phenomenon.

VI. Conclusion and Future Work

In this paper, we have discussed how the tiny yet real happiness phenomenon may influence people's mobile game usage and spending behavior, and supported our conjectures using real-world datasets from App Annie, the World Values Survey, among others. We found that that, surprisingly, countries with longer work hours, higher Gini scores, lower unemployment rates, and lower levels of life satisfaction were all associated with higher spending on mobile gaming on a per-user basis. We believe that such findings merit the attention of the mobile gaming industry as well as researchers in computational psychology, labor economics, and related fields.

Some future directions may be useful in further confirming and refining the present findings. First, our future models will include more behavioral information, such as how particular mobile games are played, for how long, and at which time points. This would allow us to explain how games are played as well as how they are paid for, and thus improve our understanding of the interaction between game play and spending behavior. Second, we plan to develop genre-specific models, to explain mobile game spending in different types of games, such as role-playing, action, puzzles, and so on. Such models could be immediately applied to refine how mobile games are marketed in different countries. Our ultimate goal, however, will use gaming behavioral data to understand more about our societies and world, and identify ways to improve them.

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