Understanding Community Mobility through Life Satisfaction, Human Development, and ICT Development: a Data Mining Approach

Gunawan
Department of Industrial Engineering, Faculty of Engineering
University of Surabaya
Surabaya, Indonesia
gunawan@staff.ubaya.ac.id

***Abstract*— Prior studies have investigated community mobility to understand the spread of Covid-19 cases, especially during the early months. The goal of this study was to explain community mobility through social measures. Three composite measures, namely the social life satisfaction index, human development index, and ICT development index, were selected as social-related measures to explain community mobility. The data mining approach was adopted using the Knime Analytical Platform as the software and the Cross-Industry Standard Process for Data Mining as a process framework. The analysis covered the mobility fluctuation among 34 provinces in Indonesia using the data from Google Mobility Report from July 2020 to August 2021. Cluster analysis with the k-medoids algorithm grouped provinces into higher and lower mobility provinces. The findings indicated an association between mobility fluctuation among provinces and the social life satisfaction index, human development index, and ICT development index. Four provinces, namely Bali, Yogyakarta, Jakarta, and Riau Islands, had higher mobility, human development index, and ICT development index. The study provides evidence of factors explaining human mobility and thus enriches the literature on human mobility and the social impact of the Covid-19 pandemic. The finding also enhances the literature on applying data mining to social research at a country level. However, the generalization of this finding is limited as the analysis covers Indonesian data only. This study could be extended to other countries to arrive at more generalizable results across countries.**

Keywords*— *Covid-19, data mining, HDI, Knime, life satisfaction, mobility

I. Introduction

The Covid-19 pandemic, which was expected to end within a few months, has unexpectedly lasted longer and approached two years. All countries have been battling against the quick-spreading nature of the virus. As the infection could be transmitted from person to person, human mobility is the main factor in spreading the virus. Therefore, the mobility limitation order, physical and social distancing, and social gathering control have been pursued by all nations to suppress the spread of the virus. While waiting for the governments to complete the vaccination programs, these actions are successful.

Social, economic, educational, leisure, and religious activities commonly involve people gathering. The movement control order has impacted those activities. Google has openly reported the community mobility for each country and its regions (e.g., province, state) since the middle of February 2020. The mobility data covers six areas: workplace, grocery-and-pharmacy, retail and recreation, transit and station, park, and residential. The data has been valuable to evaluate the effectiveness of mobility control imposed by the government, such as the case in Germany [1], the U.S. [2], and India [3]. Besides government directives, voluntary social distancing decreased human mobility [4].

The spread of Covid-19 cases has been investigated to find the basis for determining a good strategy to restrain it. Investigation of the number of Covid-19 cases during the early pandemic confirmed that Human Development Index (HDI) is the most significant indicator associated with that number [5]. However, another measure is required to logically explain the relationship between HDI and the cases. During the early months of the pandemic, other studies indicated that nations and cities with highly globalized orientation, a high urbanization rate, and increased human mobility experienced a higher rate of Covid-19 cases [6]. Therefore, the possible sound association is that the community with high HDI has high mobility, then high mobility relates to the increasing cases of Covid-19. In addition, HDI and the level of the urban population are associated with the number of Covid-19 testing conducted [7]. Here, HDI reflects the governments' capacity to encounter the pandemic.

The American Psychological Association (APA) defines life satisfaction as "the extent to which a person finds life to be rich, meaningful, full, or of high quality." The OECD Better Life indicates that the survey method could collect a personal evaluation of an individual's health, education, income, personal fulfillment, and social conditions (oecdbetterlifeindex.org). In addition to personal factors, life satisfaction is influenced by societal conditions [8]. As personal perspective and social circumstance are different among countries, there is no agreement regarding the components and the critical level of satisfaction measures across societies with other cultures. For example, in Asia, marital status, the standard of living, and the role of government might have a more significant effect than income on life satisfaction [9]. Though life satisfaction relates to social aspects, no prior study linked it with community mobility.

Internet penetration or Internet use is often placed as a social-economic indicator. Prior studies have provided evidence of the benefit of Internet use, such as in Mexico [10], South Africa [11], and Indonesia [12]. The availability of Internet facilities comes from the Information and Communication Technology (ICT) development. ICT is a structural element in making a modern society, and its practical use generates social and economic benefits to the community [13]. While internet (ICT in general) use could stimulate social and economic activities, its relationship with human mobility has not been explored.

Most studies investigating Google's mobility data used the first few months of the data to assess its pattern against government-imposed movement control. The first few months of the pandemic could be considered a 'turbulent period.' The immediate government order impacts the sharp decrease of mobility change. After a few months, people adapted themselves to the condition. The prolonged movement control policy has been more relaxed or focused on smaller regions than the country. This condition might lead the mobility pattern to become more stable. The investigation of the mobility patterns among regions showed the differences. This characteristic opened an opportunity for further exploration and to answer the intriguing question, "Does the mobility fluctuation in regions could be explained by some social measures?"

This study focused on investigating Indonesia's community mobility fluctuation using the data, not from the beginning of the pandemic, but from Jul 1st, 2020 to Aug 31st, 2021, to get a more stable change. The first objective was to identify the characteristics of mobility fluctuation among all 34 provinces. The second objective was to find an association between mobility fluctuation and three social measures: human development index, life satisfaction index, and ICT development index among 34 provinces.

The remainder of the study continues as follows: Section II discusses the variables, framework, and data source; Section III presents the findings. Finally, the last section concludes and proposes corresponding implications.

II. Method

This study belongs to secondary and quantitative research. The Knime Analytical Platform, open-source software for data mining, was used for analysis. The data analysis process followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework [14]. It comprised six phases of the data science life cycle: Business understanding, Data understanding, Data preparation, Modelling, Evaluation, and Deployment. In this study, the first phase, business understanding, was adapted into research understanding, referring to the data mining objective.

This study investigated four variables. The first was community mobility, represented by the Community Mobility Reports released by Google [15]. The data contained the human mobility change during the pandemic compared to before the pandemic. The baseline of the normal period before the pandemic was the median value, for the corresponding day of the week, during the five weeks from Jan 3rd–Feb 6th, 2020. The daily data portrayed fluctuation over time by geography across six different categories of places: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential, as stated earlier. The second variable was the Human Development Index (HDI), a statistic composite index of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable, and having a decent standard of living [16]. The index between countries is published annually by the United Nations Development Programme.

Furthermore, the third variable was the Life Satisfaction Index (LSI), a global measure to compare countries, but some versions of the index were used. In the Indonesian context, the Life Satisfaction Index consists of Social Life Satisfaction Index (SLSI) and Personal Life Satisfaction Index, as defined by the Indonesian Central Bureau of Statistics (BPS). This study adopted the SLSI only, which comprised five satisfaction measures on social relationship, family harmony, leisure time, environmental condition, and safety condition.

Finally, the fourth variable was the ICT Development Index (IDI), a global measure for ICT development between countries. The index is published annually by the United Nations International Telecommunication Union [17]. IDI comprises three sub-index: ICT access, ICT use, and ICT skills consisting of 11 measures such as percentage of households with internet access, percentage of individual use internet, and mobile broadband subscription.

Those four variables were formed into a research framework shown in Figure 1. It shows the expected association between mobility fluctuation and the other three variables. The first study objective referred to the investigation of mobility fluctuation. While the second was to investigate the relationship between mobility fluctuation, Human Development Index (HDI), Social Life Satisfaction Index (SLSI), and ICT Development Index (IDI) among provinces. The four variables have an interval scale, and none was treated as a dependent variable. Therefore, the data mining technique adopted was the classification or clustering under the unsupervised learning model.

The data source and period for the four measures are presented in Table 1. Data on community mobility for Indonesia was obtained from Google's site. HDI, SLSI, and IDI were collected from the statistical report published by the Indonesian Central Bureau of Statistics (BPS). The latest data for SLSI was the year 2017. However, it was still relevant as the investigation did not aim to identify the current social life satisfaction rather than the variation of this index among provinces.

III. Result and Discussion

A. Characteristics of community mobility

The graphical analysis of mobility fluctuation among six areas (not presented in this paper) indicated the different intensities. Except for the residential area, the mobility fluctuation for all five areas had negative values. It means that fewer people did activities during the pandemic than before. On the other hand, the positive mobility fluctuation in residential areas could be interpreted as more people at home than before the outbreak. This condition was caused by the government policy "work from home" and "study from home."

The root-mean-square (RMS) of mobility fluctuation was calculated for six areas per province. The average RMS for all provinces was calculated and presented in Table II. It shows that transit stations experienced the highest mobility fluctuation but the lowest in the residential area. The government-imposed movement control order or lock-down policy impacted the decreasing of people's mobility. Furthermore, the traveling limitation policy and the closure of public transportation decreased people's activity in train and station areas. Figure 2 presents the line plot for the transit station area as a sample of six areas. Daily mobility data were combined into weekly for better picturing. The most significant drop was experienced by Bali province. The slightest fluctuation and recently to be positive was Gorontalo province.

Furthermore, the total mobility per province was calculated from the mean score of six areas. Table III shows the top three provinces with the highest total mobility fluctuation: Bali, Jakarta, and Yogyakarta. Those provinces have high people mobility before the pandemic. It is noted that Jakarta is the capital city of Indonesia, while Bali and Yogyakarta are the top international and domestic tourist destinations. Various mobility limitation policies were likely to lower the community mobility considerably. The table presents three provinces with the lowest mobility fluctuation: Central Sulawesi, South-East Sulawesi, and Central Kalimantan. These provinces seemed to have low people mobility before the pandemic. For example, the mobility fluctuation of Bali was 2.5 times that of Central Kalimantan.

Calculating total mobility fluctuation is helpful as the community experienced mobility fluctuation in all six areas. Figure 3 presents the line plot of total mobility. The high score of total mobility indicated that a province experienced high mobility fluctuation. Figure 3 marks Bali as a province with the highest mobility fluctuation and Central Kalimantan with the lowest. The sharp peak of mobility fluctuation in June-July-August 2021 indicated the impact of the mobility control policy due to the spread of the Covid-19 Delta variant.

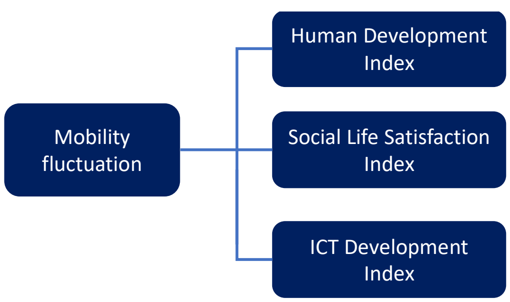

Fig. 1. Research framework.

TABLE I. DATA SOURCE

Measures	Source	Period	Range
Community mobility	Google	Jul 2020 – Aug 2021	-
Human Development Index	BPS[18][a]	2020	1-100
Social Life Satisfaction Index	BPS[18]	2017	1-100
ICT Development Index	BPS[19]	2020	1-10

[a] BPS: Badan Pusat Statistik (the Central Bureau of Statistics)

TABLE II. AVERAGE MOBILITY OF EACH AREA

Area	average RMS	Area	average RMS
transit stations	31.1	grocery and pharmacy	18.3
workplace	25.6	retail and recreation	15.9
parks	19.4	residential	7.2

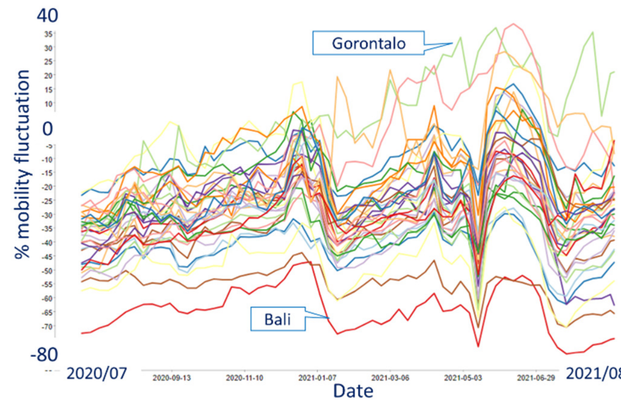

Fig. 2. Mobility at transit stations.

TABLE III. TOTAL MOBILITY SCORE AMONG PROVINCES

Top three	mobility (%)	Bottom three	mobility (%)
Bali	36.7	Central Sulawesi	15.9
Jakarta	30.6	South-East Sulawesi	15.7
Yogyakarta	25.7	Central Kalimantan	14.4

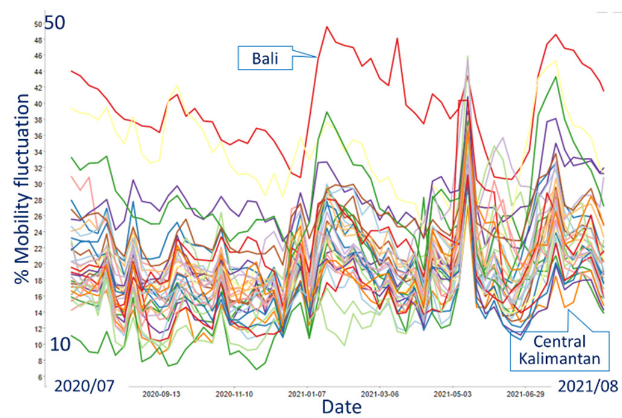

Fig. 3. Total mobility fluctuation.

B. *Cluster analysis*

Further analysis was to identify the relationship among total mobility fluctuation, HDI, SLSI, and IDI among provinces. Linear correlation was conducted to find the association between variables. Table IV shows that SLSI had a slight negative correlation with the other three variables, and these correlations are statistically not-significant (p-value >0.05). On the other hand, a high correlation appeared for HDI and IDI. It denotes that province with higher HDI also tends to have more ICT development. Furthermore, the result indicated that provinces with high mobility tended to have higher HDI and IDI.

Clustering analysis was performed to group provinces based on the similarity of the values from the four variables. Considering the number of objects was only 34 provinces, a simple k-means or k-medoids (a variant of k-means) clustering algorithm was considered. K-means is sensitive if data presents some outliers, and k-medoids are more appropriate for this condition [20]. Figure 4 illustrates Knime's workflow for k-medoid clustering. The workflow comprised primary nodes for reading data, calculating correlations, doing k-medoids clustering, and calculating the Silhouette coefficients.

The choice of k as cluster size needs to be determined in advance. The number of k was evaluated using the Silhouette coefficient, a metric (value from -1 to 1) used to assess the goodness of a clustering technique. Table V displays the mean scores of the Silhouette coefficient for k = 2,3,4. The highest mean score (0.653) was for k=2, and both composing Silhouette coefficients were considerably high (0.680, 0.457). Therefore, k=2 was determined for clustering.

The clustering with the k-medoids algorithm has grouped provinces into two groups with 4 and 30 provinces. The number of provinces for both clusters indicates disparity. The normalized mean score with value ranges from 0 to 1 was calculated for four variables, as presented in Table VI, to compare both clusters. Four provinces in cluster A had higher mobility fluctuation, HDI, and IDI, but lower SLSI, than 30 provinces in cluster B. While the correlation between SLSI and the other three variables was not statistically significant, the cluster analysis indicated the difference in SLSI mean scores between the two clusters. This finding empirically provides evidence about the association among those four variables among regions.

Table VII presents the list of provinces in each cluster. First, cluster A comprised only four provinces: Jakarta, Bali, Yogyakarta, and Riau Islands. Jakarta is the capital city of Indonesia, while Bali and Yogyakarta are the major international and domestic tourist destinations. Riau Islands has Batam city with high economic activities. More than half of the Riau Islands population resides in Batam, with a population density of 1,206 people per km sq. in 2020. These four provinces indicated high community mobility before the pandemic. Second, cluster B contains 30 provinces with mixed characteristics. It covers all provinces in Java (except Jakarta) with high population density and provinces with low population density, such as Papua and West Papua.

Furthermore, Fig. 5-7 presents provinces' graphical position within the two clusters. Figure 5 shows that the difference between the two clusters was apparent but not too strong. Provinces in cluster A have higher mobility fluctuation than those in cluster B. Cluster A has low SLSI, but cluster B has low to high SLSI. Therefore, the difference between both clusters is not significant. Furthermore, Fig. 6 indicates that provinces in cluster A had higher mobility and HDI than cluster B. The association between mobility and HDI was supported by a prior study that found an association between HDI, mobility, and the number of Covid-19 cases [6]. Similarly, Fig. 7 shows that four provinces in cluster A had higher mobility and ICT development index than those in cluster B. It means that regions with high mobility fluctuation are associated with high ICT development.

In summary, the finding indicates that provinces with high community mobility fluctuation are strongly associated with high human development index and ICT development index; and slightly related to low social life satisfaction index. On the other hand, provinces with low community mobility fluctuation tend to have a low level of human development index and ICT development index.

TABLE IV. CORRELATION

Variable	Corr.	Variable	Corr.
mobility-HDI	0.52	HDI -SLSI	-0.12*)
mobility-SLSI	-0.10*)	HDI -IDI	0.94
mobility-IDI	0.59	SLSI-IDI	-0.16*)

*) non-significant with p-value <0.05

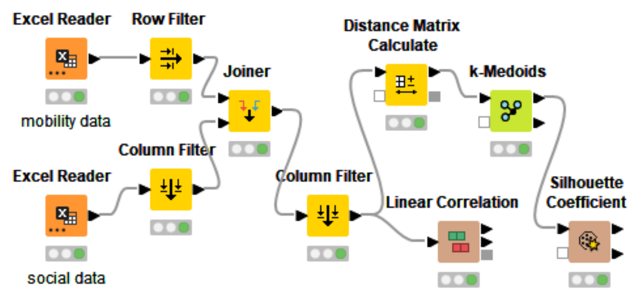

Fig. 4. Knime's workflow for clustering.

TABLE V. EVALUATION OF CLUSTER SIZE

K	cluster size	Mean Silhouette coef. each cluster	Mean Silhouette coef. Overall
2	4,30	0.680, 0.457	0.653
3	4,9,21	0.431, 0.138, 0.489	0.389
4	4,8,9,13	0.102, 0.065, 0.102, 0.275	0.197

TABLE VI. NORMALIZED MEAN

cluster	Mobility	HDI	SLSI	IDI
Cluster A (4 provinces)	0.704	0.862	0.291	0.863
Cluster B (30 provinces)	0.171	0.471	0.438	0.495

TABLE VII. CLUSTER MEMBERSHIP

Cluster A (4 provinces)		
Bali	Jakarta	Riau Islands
Yogyakarta		
Cluster B (30 provinces)		
Aceh	Central Java	North Sulawesi
North Sumatra	East Java	Central Sulawesi
West Sumatra	Banten	South Sulawesi
Riau	West Nusa Tenggara	South East Sulawesi
Jambi	East Nusa Tenggara	Gorontalo
South Sumatra	West Kalimantan	West Sulawesi
Bengkulu	Central Kalimantan	Maluku
Lampung	South Kalimantan	North Maluku
Bangka Belitung	East Kalimantan	West Papua
West Java	North Kalimantan	Papua

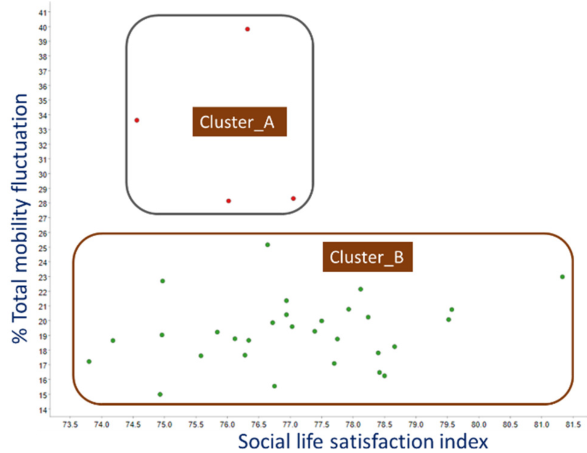

Fig. 5. Cluster members for Mobility vs. Social life satisfaction index.

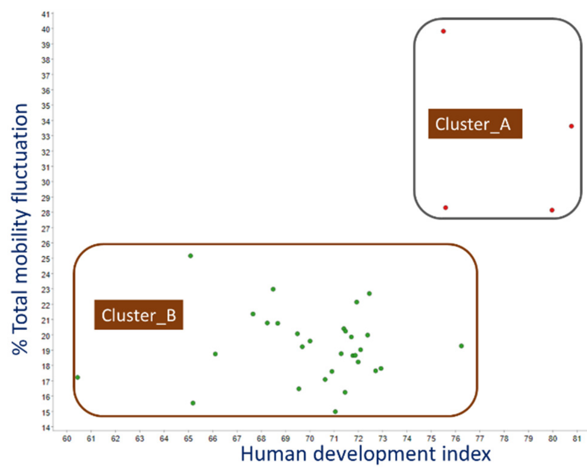

Fig. 6. Cluster members for Mobility vs. Human development index.

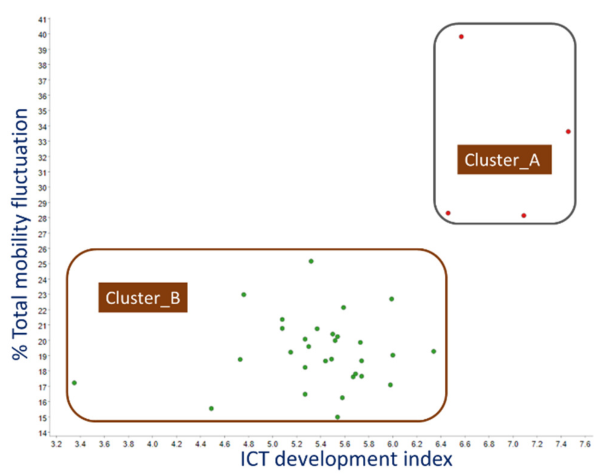

Fig. 7. Cluster members for Mobility vs. ICT development index.

IV. Conclusion

This study explored whether community mobility could be explained through some social measures. The result indicated the characteristics of mobility fluctuation among provinces in Indonesia using data Google Mobility Report from July 2020 to August 2021. The finding showed the association between mobility fluctuation among provinces and the social life satisfaction index (SLSI), human development index (HDI), and ICT development index (IDI). Provinces with higher mobility had higher human development index and ICT development index. On the other hand, these provinces have a slightly lower social life satisfaction index. The result affirmed that some social measures could explain community mobility. Moreover, the clustering indicated that most provinces have lower mobility fluctuation, lower HDI and IDI, and slightly higher SLSI.

This study, firstly, suggests the provincial government with high mobility fluctuation (cluster A) to take cautious action to tighten or loosen the mobility limitation policy because those provinces were vulnerable to mobility change. Secondly, in the short term, the provincial governments of cluster B might observe the mobility fluctuation. Because the low mobility fluctuation indicates, people change little their mobility compared before the pandemic. As the HDI score could reflect the local government capacity, the support from the central government to fight the Covid-19 pandemic, especially to provinces with low HDI, is highly needed.

This study enriches the literature on human mobility as the finding provides evidence of social factors explaining community mobility. Moreover, this study enhances the literature on applying data mining to social research at a country (macro) level. However, the generalization of this finding is limited as this study used only Indonesian data. As Google mobility report is available for all countries and their regions, further studies are highly possible.

References

[1] T. Hartl, K. Wälde, and E. Weber, “Measuring the impact of the German public shutdown on the spread of COVID-19,” 2020. [Online]. Available: https://voxeu.org/article/measuring-impact-german-public-shutdown-spread-covid-19.

[2] A. Brzezinski, G. Deiana, V. Kecht, and D. Van Dijcke, “The COVID-19 Pandemic: Government vs. Community Action Across the United States,” 2020. [Online]. Available: https://osf.io/preprints/socarxiv/s9k4y/.

[3] J. Saha, B. Barman, and P. Chouhan, “Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020,” *Child. Youth Serv. Rev.*, vol. 116, no. June, 2020.

[4] W. Maloney and T. Taskin, “Voluntary vs. mandated social distancing and economic activity during COVID-19,” 2020. [Online]. Available: https://voxeu.org/article/covid-social-distancing-driven-mostly-voluntary-demobilisation.

[5] I. Sirkeci and M. Murat Yüceşahin, “Coronavirus and migration: Analysis of human mobility and the spread of covid-19,” *Migr. Lett.*, vol. 17, no. 2, pp. 379–398, 2020.

[6] T. Sigler *et al.*, “The socio-spatial determinants of COVID-19 diffusion: the impact of globalization, settlement characteristics and population,” *Global. Health*, vol. 17, no. 1, pp. 1–14, 2021.

[7] M. E. Marziali, R. S. Hogg, O. A. Oduwole, and K. G. Card, “Predictors of COVID-19 testing rates: A cross-country comparison,” *Int. J. Infect. Dis.*, vol. 104, pp. 370–372, 2021.

[8] E. Diener, R. Inglehart, and L. Tay, “Theory and Validity of Life Satisfaction Scales,” *Soc. Indic. Res.*, vol. 112, no. 3, pp. 497–527, 2013.

[9] Y. T. Ngoo, N. P. Tey, and E. C. Tan, "Determinants of Life Satisfaction in Asia," *Soc. Indic. Res.*, vol. 124, no. 1, pp. 141–156, 2015.

[10] J. Mora-Rivera and F. García-Mora, "Internet access and poverty reduction: Evidence from rural and urban Mexico," *Telecomm. Policy*, vol. 45, no. 2, p. 102076, 2021.

[11] M. Salahuddin and J. Gow, "The effects of Internet usage, financial development and trade openness on economic growth in South Africa: A time series analysis," *Telemat. Informatics*, vol. 33, no. 4, pp. 1141–1154, 2016.

[12] R. Imansyah, "Impact of internet penetration for the economic growth of Indonesia," *Evergreen*, vol. 5, no. 2, pp. 36–43, 2018.

[13] M. Dobrota, V. Jeremic, and A. Markovic, "A new perspective on the ICT Development Index," *Inf. Dev.*, vol. 28, no. 4, pp. 271–280, 2012.

[14] F. Martinez-Plumed *et al.*, "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories," *IEEE Trans. Knowl. Data Eng.*, vol. 33, no. 8, pp. 3048–3061, 2019.

[15] Google, "COVID-19 Community Mobility Reports," 2021. https://www.google.com/covid19/mobility.

[16] UNDP, "Human Development Index (HDI)," *United Nations Development Programme*, 2020. http://hdr.undp.org/en/content/human-development-index-hdi (accessed Sept 1st, 2021).

[17] ITU, "The ICT Development Index (IDI): conceptual framework and methodology," *International Telecommunication Union*, 2017. https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2017/methodology.aspx (accessed Sept 1st, 2021).

[18] BPS, "Statistical Yearbook of Indonesia 2021," *Badan Pusat Statistik*, 2021.

[19] BPS, "Monthly Report of Social-Economic Data: August 2021," *Badan Pusat Statistik*, 2021.

[20] P. Arora, Deepali, and S. Varshney, "Analysis of K-Means and K-Medoids Algorithm for Big Data," *Procedia Comput. Sci.*, vol. 78, pp. 507–512, 2016.

Proceedings

Edited by Vo Nguyen Quoc Bao and Luong Duy Manh

2021 8th NAFOSTED Conference on Information and Computer Science (NICS)

NICS 2021

December 21-22, 2021
Hanoi, Vietnam

2021 8th NAFOSTED Conference on Information and Computer Science (NICS) | 978-1-6654-1001-4/21/$31.00 ©2021 IEEE | DOI: 10.1109/NICS54270.2021.9701557

Welcome

Opening Speech

Prof. TRAN XUAN NAM, Vice - President of Le Quy Don Technical University

Colleagues, Guests, Ladies and gentlemen,

It is my great pleasure to welcome you to the 8th NAFOSTED Conference on Information and Computer Science - NICS 2021 which is hosted by the Le Quy Don Technical University. I know that many of you are from many countries around the world; welcome you to NICS 2021!

I would like to take this opportunity to express my gratitude to sponsor agencies, in particular:

- IEEE Systems
- National Foundation for Science and Technology Development (NAFOSTED)

I do hope that our relationship will be stronger via such cooperative activities. Also, my very special thanks go to the people of the Organizing Committee and Programme Committee for all their work without which we would not be here, in this virtual conference.

Ladies and Gentlemen,

Le Quy Don Technical University was established in 1991 based on the Military Technical Academy. It operates as a public university providing education for both civilians and military personnel. Since its establishment, the university has quickly become one of the leading universities in Engineering & Technology in Vietnam. Our aspiration is to have our research and teaching institution being recognized at the international level.

This aspiration is reflected in its consistent success in gaining external competitive research grants; its ability to attract outstanding students to its undergraduate, postgraduate coursework, and postgraduate research programs. In 2008, the government recognized our university as one of the key national universities. An indication of the size and dimensions of the university can be gained from the following statistics: we have 15 engineering faculties/institutes and 12 research centers, over 10,000 students, and about 900 permanent academic staff.

We have close links with the community and continue to play a leading role in, and attract support from Vietnamese society. Additionally, the university maintains a firm international standing by fostering cooperative research linkages and staff and student exchanges with many international universities.

I am, as the vice-president of the university, particularly interested in the idea of hosting NICS 2021 proposed by the Faculty of Radio-Electronic Engineering. These events are organized to provide an opportunity for researchers from academia and industry to meet and discuss the latest ideas, solutions, and scientific results in the fields of Electronics, Information, and Computer Science. Also, I believe that such activities will be an excellent opportunity to boost our international collaboration programs.

Now let me finally wish you successful conferences with interesting presentations and lively discussions.

Thank You!

Committees

Honorary Co-Chairs

Nguyen Cong Dinh (Le Quy Don Technical University, Vietnam)

Tu Bao Ho (Japan Advanced Institute of Science and Technology, Japan)

Secretary

Vu Van Minh (The National Foundation for Science and Technology Development (NAFOSTED), Vietnam)

Linh Thuy Nguyen (Le Quy Don Technical University, Vietnam)

Steering Co-Chairs

Xuan Nam Tran (Le Quy Don Technical University, Vietnam)

Koichiro Ishibashi (The University of Electro-Communications, Japan)

General Co-chairs

Ta Chi Hieu (Le Quy Don Technical University, Vietnam)

Cong-Kha Pham (University of Electro-Communications (UEC), Japan)

Mohammad Tariqul Islam (Universiti Kebangsaan Malaysia, Malaysia)

Technical Program Co-chairs

Vo Nguyen Quoc Bao (Posts and Telecommunications Institute of Technology, Vietnam)

Khuong Ho Van (HoChiMinh City University of Technology, Vietnam)

Luong Duy Manh (Le Quy Don Technical University, Vietnam)

Publications Co-Chairs

Hung Nguyen Tan (Danang Uni. of Science & Technology, Vietnam)

Nguyen Van Trung (Le Quy Don Technical University, Vietnam)

Publicity Co-Chairs

Nguyen Quoc Dinh (Le Quy Don Technical University, Vietnam)

Huynh Binh (Ha Noi University of Science and Technology, Viet Nam, Vietnam)

Jiri Vesely (University of Defence, Czech Republic)

Local Co-Chairs

Hoang-Gia Vu (Le Quy Don Technical University, Vietnam)

Nguyen Minh Giang (Le Qui Don University, Vietnam)

Phat Tien Nguyen (Le Quy Don Technical University, Vietnam)

Nguyen Tien Thai (Le Qui Don University, Vietnam)

Financial Co-Chair

Thu Phuong Nguyen (Le Quy Don Technical University, Vietnam)

Keynote Co-Chairs

Xuan-Tu Tran (VIetnam National University, Hanoi, Vietnam)

Van-Phuc Hoang (Le Quy Don Technical University, Vietnam)

Communication and Networking

Duc-Hung Le (The University of Science Ho Chi Minh City, Vietnam)

Toan Dao (University of Transport and Communications, Vietnam)

Quang Kien Trinh (Le Quy Don Technical University, Vietnam)

Computational Intelligence

Xuan-Tung Truong (Le Quy Don Technical University, Vietnam)

Michishita Naobumi (National Defense Academy, Vietnam)

Foundations of Computer Science

Le Sy Vinh (VNU Ha Noi, Vietnam)

Quang Uy Nguyen (Le Quy Don Technical University, Vietnam)

Software Engineering

Chi Dinh Nguyen (FPT University, Vietnam)

Khanh Quoc Nguyen (Le Quy Don Technical University, Vietnam)

Table of Contents

Computational Intelligence

Communication and Networking

2021 8th NAFOSTED Conference on Information and Computer Science (NICS) | 978-1-6654-1001-4/21/$31.00 ©2021 IEEE | DOI: 10.1109/NICS54270.2021.9701457

Keynote speaker #1: CRYScanner: Finding cryptographic libraries misuse

Computational Intelligence

Computational Intelligence

Indexed by Scopus

https://www.scopus.com/authid/detail.uri?authorId=57212047447

Conference Paper • *Open access*

Understanding Community Mobility through Life Satisfaction, Human Development, and ICT Development: A Data Mining Approach

Gunawan

Proceedings - 2021 8th NAFOSTED Conference on Information and Computer Science, NICS 2021, 2021, pp. 236–241

Show abstract   Related documents

Publikasi di IEEE Xplore

https://ieeexplore.ieee.org/document/9701574

Conferences > 2021 8th NAFOSTED Conference ...

Understanding Community Mobility through Life Satisfaction, Human Development, and ICT Development: a Data Mining Approach

Publisher: IEEE   Cite This   PDF

Gunawan   **All Authors**