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The Nonlinear Influences of Natural Gas Consumption, Thermal Electricity and Renewable Electricity on Carbon Emissions

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ABSTRACT

This study examines the nonlinear influences of natural gas consumption, thermal electricity, and renewable electricity on carbon emissions by means of the panel data of 32 countries in OECD in the period of 1993-2010. This study applies artificial neural network (ANN) technique to undertake the empirical research. The results show natural gas consumption has an inverse U-shaped effect on carbon emissions. Besides, thermal electricity has a positive effect on carbon emissions. In addition, this study finds out that renewable electricity has a negative influence upon carbon emissions. Hence, the development of renewable electricity is one of the most effective approaches to reduce carbon emissions. Furthermore, the reduction of thermal electricity can significantly decrease carbon emissions.

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INTRODUCTION

Due to financial crisis, the economy downturn reduced global carbon emissions in 2008 such that the global carbon emissions dropped 1.3% in 2009 (International Energy Agency, 2012). In 2010, the global carbon emissions reached a new high according to a report by the International Energy Agency (IEA) (International Energy Agency, 2012). The global carbon emission reached 3,160 million tons in 2010 (International Energy Agency, 2012). Due to the greenhouse effect, it is urgent that countries should use alternative energy in order to eliminate to environmental pollution, natural environment damage, and carbon emissions. In 2010, United Nations Framework Convention on Climate Change (UNFCCC) formed an agreement in which 193 countries would like to keep the global warming less than 2 degrees Celsius (International Energy Agency, 2012). Global warming causes a higher sea level, living problems on islands, damages to the environment, and unusual storms and drought in the world. The greenhouse gases (GHG) which include CO2, CH4, N2O, PFCs, HFCs, SF6, and other greenhouse gases are one of the major sources of the greenhouse effect. Because Carbon Dioxide accounts for 55% of carbon emission (International Energy Agency, 2012), it is crucial that every country do their best to eliminate the emission of Carbon Dioxide.

After the oil crisis in 1970s, most major countries aggressively looked for new energy resources, promoted the policy of carbon emission elimination, and funded research of renewable energy (Chen and Chang, 2013a). In 2009, UNFCCC estimated the renewable energy will supply approximately 40% of global energy by 2050 (Pernick *et al.*, 2012). In the report of Clean Energy Trends 2012, Pernick *et al.* (2012) argue that bio-fuel energy, wind power, and solar power would grow rapidly in the renewable energy industries. These three major renewable energies in the global energy production would grow from 56.4, 60.5, and 71.2 billion dollars in 2010 to 112.8, 112.9, 113.6 billion dollars in 2020, and average growth rate would be 7.2%, 6.4%, and 4.8%, respectively (International Energy Agency, 2012). Due to several disasters such as the Japanese earthquake and tsunami in 2011, the world has concerned about the negative impact of nuclear energy such that a new demand for renewable resources is increasing.

In the future, renewable energy could reduce the dependence on fossil fuels and bring a new balance between environmental protection and economic development. Besides renewable electricity, natural gas and thermal electricity are two of major sources of global energy (Pernick *et al.*, 2012). There is no research exploring the nonlinear influences of natural gas consumption, thermal electricity, and renewable electricity on

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carbon emissions. In order to help countries to develop their energy policy and reduce their carbon emissions, the purpose of this study is to investigate the nonlinear influences of natural gas consumption, thermal electricity, and renewable electricity on carbon emissions from the data of 32 countries in OECD to fill the research gap. This study applies an artificial neural network (ANN) technique to analyze the panel data in the period of 1993-2010.

Literature Review:

The influence of natural gas consumption:

After the Industrial Revolution, the use of fossil fuels is beneficial for the economic development in the world. Using fossil fuels has caused an unnatural global warming which results in climate change, because burning fossil fuels would produce CO_2, CH_4, N_2O, PFCs, HFCs, SF_6, and other greenhouse gases (Das and Veziroglu, 2001). Currently, fossil fuels still contribute to the majority of energy consumption in the world, but people will face problems of serious environmental pollution, the shortage of fossil fuels, and a global energy crisis within several decades (Dorian *et al*., 2006). Comparing the carbon emissions of fossil fuel energy production, the carbon emissions produced by natural gas are 1.3 pounds per kWh is lower than those produced by coal and oil which are 2.1 and 1.9 pounds per kWh in 2008, respectively (Lafrancois, 2012). Prior research thinks that natural gas plays an important role in reducing the demand of coal and gas (Hultzler and Kendell, 1999). In the past decade, new natural gas power plants have been broadly built in America, because they are low cost, fast construction, and can be operated with less environmental pollution (Smead, 2010). Besides, the price of natural gas is affected by the demand and supply of fossil fuels in the world. When the price of natural gas goes up, it will encourage the investment in coal power plants (Van Vuuren and Riahi, 2008). If there is not a proper climate policy in the world, it is difficult for the popularity of new natural gas power plants, and this will increase the usage of thermal power plants and increase carbon emissions (Van Ruijven and Van Vuuren, 2009). Therefore, natural gas power plants can reduce carbon emissions from environmental protection reasons (Aune *et al*., 2004; Lafrancois, 2012). The first purpose of this study is to investigate the nonlinear relationship between natural gas consumption and carbon emissions by means of artificial neural network (ANN).

The influence of thermal electricity:

The generation of electricity is important to the development of economy. Under the rising economy, the demand of electricity would raise (Charles, 1991), but the increase of the power generation could cause a severe impact on the environment (Kim, 2007). Currently, one third of carbon emissions come from power generation since fossil fuels are the major energy of power generation (Ang *et al*., 2011). Using a lot of fossil fuels to generate power causes an enormous influence on the environment. Most of thermal electricity generation could produce toxic gas which can pollute the air (Kayin *et al*., 1999). As a result, one of the major sources for global warming and acidic materials accumulation in the world is the use of fossil fuels (Joskow, 2003; Lora and Solomon, 2005). In order to protect the environment, previous research thinks thermal power plants have to disclose more information about their carbon emissions in their environmental accounting (Liu, 2009). Because fossil fuels are main energy of thermal electricity generation, the usage of thermal power plants would impact the prices of raw materials and fuels which could influence the development of other industries (Ghash *et al*., 2012). Hence, thermal power generation does not only affect the environment, but also influence the operation and development of other industries (Lora and Solomon, 2005). The second purpose of this study is to investigate the nonlinear relationship between thermal electricity and carbon emissions by means of artificial neural network (ANN).

The influence of renewable energy:

After the formulation of Kyoto Protocol in 1997, people become aware of the importance for replacing fossil fuels with other clean renewable resources (Chen and Chang, 2013b). The problem about the increasing carbon emissions could not be neglected any more. Carbon emissions are one of the serious problems in the world (Haliciouglu, 2009; Wang, 2013). Since 1970, the price of fossil fuels went higher and higher, so people started noticing the importance of renewable energy (Sadorsky, 2006). Renewable energy is defined as the energy which we can get from the natural environment and is inexhaustible (Palmer and Burtraw, 2005). Renewable energy, such as solar energy, wind energy, hydroelectric energy, tidal energy, wave energy, and biomass energy, can be generated in a process of fewer carbon emissions (Aflaki and Netessine, 2012). Besides, renewable energy could reduce the economic impact on the price of fossil fuels (Awerbuch and Sauter, 2006).

Prior literature claims that renewable energy could eliminate environmental pollution, lower the demand for imported fuel, and benefit environmental protection and energy supply (Komor and Bazillian, 2005; Carlei *et al*., 2011). Previous research argues that there is a positive relationship between renewable energy and GDP (Sadorsky, 2009a; Sadorsky, 2009b; Apergis and Payne, 2010). In addition, past literature asserts that renewable energy can reduce carbon emissions (Palmer and Burtraw, 2005; Aflaki and Netessine, 2012). The third purpose of this study is to investigate the nonlinear relationship between renewable energy and carbon emissions by means of artificial neural network (ANN).

Methodology and Methods:
Artificial neural network (ANN):

Complexity and uncertainty within a system would make the relationships between variables more complicated. Thus, the general pattern between variables is nonlinear rather than linear (Chen and Chang, 2010b; Chen *et al*., 2012). Thus, exploring the nonlinear relationships between variables is important not only in the field of engineering, but also in the field of energy. Because there is complexity and uncertainty in a system, traditional mindset about linear relationships between variables in the field of energy is not always effective (Poornashankar and Pawar, 2011a). Considering the complex and uncertain essence is so important in the academic areas, because the patterns of the relationships between carbon emissions and its antecedents are not always linear (Tian *et al*., 2010). However, there is few studies in the field of energy explores whether the patterns of the relationships between carbon emissions and its three antecedents, natural gas consumption, thermal electricity, and renewable electricity, are nonlinear by means of ANN (Poornashankar and Pawar, 2011b). Therefore, this study would like to explore the nonlinear effects between carbon emissions and its three antecedents to fill the research gap.

Artificial neural network (ANN) which has been one of popular tools for several years in the academic communities is a computational approach for pattern interpretation and prediction (Nayak *et al*., 2004). An ANN model imports a set of inputs and produces a corresponding set of outputs based on the relationships and connection weights in the neural network (Wasserman, 1994). There are two steps in ANN: “training (or learning)” and “testing (or predicting)”. Data are divided into two portions. The first portion is used to train the network and the second one is utilized to test the forecasting ability of the network. In the training step, the network adjusts the weights between the nodes to ‘learn’ the new knowledge. In the testing step, the network weights are applied to test forecasting outcomes of the network (Chen and Chang, 2013). After over thousands of iterations, convergence happens and the optimal weights can be obtained (Wray *et al*., 1994). The back-propagation network proposed by Rumelhart *et al*. (1986) is one of the most popular approaches in the area of ANN (Fausett, 1994; Haykin, 1994). Therefore, the back-propagation network is used in this paper.

The academic field widely uses a back-propagation network to solve problems by means of supervised learning. The network alters the weights of the connections to learn the new information in order to minimize the errors between the estimated outcomes and the actual ones (White, 1989). As reported in Fig. 1, a back-propagation neural network often applies three or more layers in the structure: an input layer, an output layer, and at least one hidden layer.

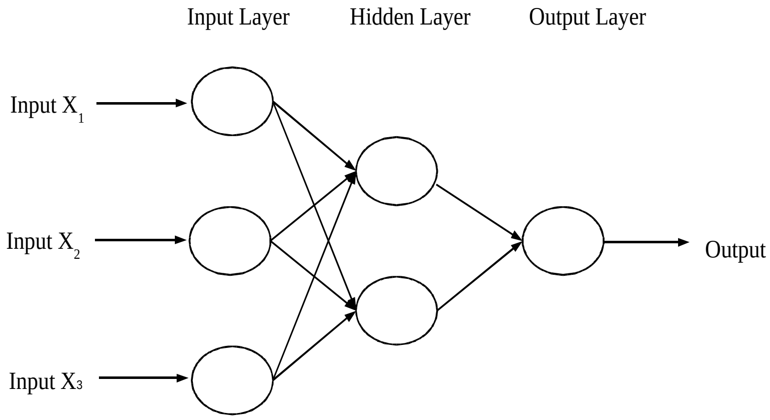

Fig. 1: Multi-layer structure of a neural network.

Because regression analysis is used under a specific requirement of the relationships between dependent and independent variables, other relationships could be neglected. Comparing to regression analysis, ANN has several advantages to discuss the relationships between variables in the following (Wray *et al*., 1994; Wanous *et al*., 2003).

- There is no previous information of the prior relationships between the input and output variables in ANN models, because the complicated relationships among them could be figured out by adjusting the weights connecting the nodes in the network (Chen and Chang, 2010a).
- Since ANN is not constrained by the assumption of linearity, the problem of multicollinearity would not occur in ANN models (Moshiri and Cameron, 2000; Chen and Chang, 2009).
- Although regression analysis can not allow missing data and perform unwell while the data are inaccurate, ANN can still work as the data are incomplete (Lippmann, 1988; Chen *et al*., 2012).

Based on the above statement, this study selects ANN, rather than regression analysis, to explore the nonlinear influences of natural gas consumption, thermal electricity, and renewable electricity on carbon emissions.

Sample and data collection:

This research mainly explores the relationships between carbon emissions and its three determinants, natural gas consumption, thermal electricity, and renewable electricity, by using the data of 32 countries in OECD in the period 1993-2010. The sample size in this study is 576. The data of this paper including the data of carbon emissions, natural gas consumption, thermal electricity, and renewable electricity are collected from the Energy Information Administration (EIA). EIA is an agency under the U.S. Department of Energy.

Measurement of the variables:

- Dependent variable - Carbon emissions. The data of carbon emissions are calculated while producing, transporting, using, disposing, and recycling products or services. Today the major carbon emissions come from coal burning and oil usage. This study employs carbon emissions as the dependent variable.
- Independent variable - Natural gas consumption. This study employs natural gas consumption as the first independent variable.
- Independent variable - Thermal electricity. This study employs thermal electricity as the second independent variable. Thermal electricity means the power generated by burning fossil fuels.
- Independent variable -Renewable electricity. This study employs renewable electricity as the third independent variable. The major resources of renewable electricity are wind power, hydroelectric power, and solar power.

Empirical Results:

The descriptive statistics are reported in Table1. ANN is applied in this study by means of Qnet200 that is a C-based simulator for developing neural network configurations and back-propagation learning algorithm. ANN models need two separate data sets. One is the training set that is utilized to train the neural net by altering the weights embedded in the network. The second data set, testing one, is applied to test the predictive ability of the neural network. According to 80-20 % principle, 80% of the sample is randomly assigned to the training set and 20% of the sample is randomly assigned to the testing set. The sample size in this paper is 576. There are 461 training data in the training set in this study. Besides, there are 115 testing data in the testing set. Hornik *et al*. (1989) assert that one hidden layer network is adequate to model any complicated system with any desired accuracy. Hence, this study adopts only one hidden layer in the ANN mode. Consequently, a general three-layer network is applied in this study. The sigmoid transfer function is utilized in the hidden nodes, and the linear transfer function is utilized in the output node. The convergence of a training set is determined by root mean squared error (RMSE) that is less than or equal to 0.0001 or a maximum of 100,000 iterations. The weights embedded in the network with the minimum of testing RMSE are considered to be optimal. As shown in Fig. 2, the convergence curves of the network errors (RMSEs) of the training and testing sets in this study are convergent after 100,000 iterations.

Table 1: Descriptive statistics.

Variables	Min.	Max.	Mean	S.D.
Natural gas consumption	0	23775	1530.1918	3907.1333
Thermal electricity	0.00188	2992.2377	173.0761	464.7913
Renewable electricity	0.06744	433.63611	49.1291	87.5314
Carbon emissions	2.45367	6015.75348	4104.3618	985.5269

As shown in Fig. 3, this study finds out that natural gas consumption has an inverse U-shaped effect on carbon emissions. There are three stages in the relationship between natural gas consumption and carbon emissions. In the first stage, there is a positive relationship between natural gas consumption and carbon emissions. It means that even though carbon emissions of natural gas are lower than those of other fossil fuels, natural gas consumption positively relates to carbon emissions in the beginning stage. In the second stage, there is no relationship between natural gas consumption and carbon emissions. It means that natural gas consumption doesn't relate to carbon emissions in the second stage. In the third stage, there is negative relationship between natural gas consumption and carbon emissions. It means that natural gas consumption negatively relates to carbon emissions in the third stage. Previous literature argues that natural gas plays an important role in reducing the demand of coal and gas (Hultzler and Kendell, 1999). Because carbon emissions of natural gas are lower than those of other fossil fuels, natural gas power plants can reduce carbon emissions in the third stage (Aune *et al*., 2004; Lafrancois, 2012). When natural gas power plants reach its full capacity of generation, carbon emissions in the world could decrease in the third stage.

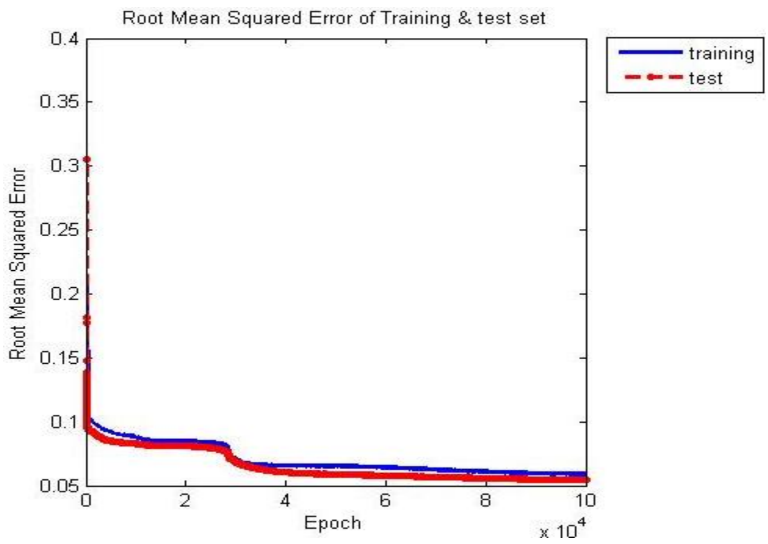

Fig. 2: The convergence curves of RMSEs of the training and testing sets.

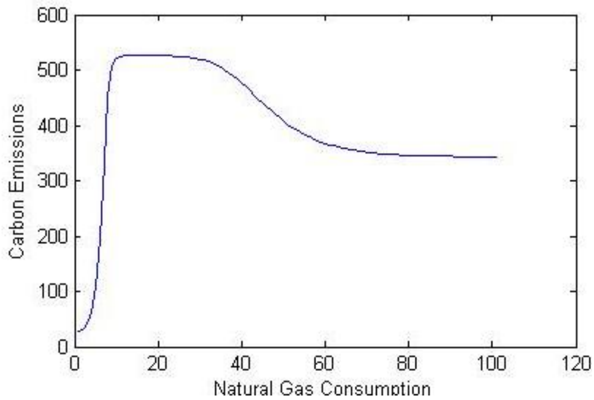

Fig. 3: The relationship between natural gas consumption and carbon emissions.

As shown in Fig. 4, there is a positive relationship between thermal electricity and carbon emissions. There are two stages in the relationship between thermal electricity and carbon emissions. Due to the need for a lot of fossil fuels in thermal electricity generation, the extent of carbon emissions goes up when the extent of thermal electricity goes up in the first stage. It means that the extent of thermal electricity positively affect the extent of carbon emissions in the first stage. In the second stage, there is no relationship between thermal electricity and carbon emissions. Due to the improvement in technology and efficiency, the progress of clean technology, and the replacement of coal with natural gas, the extent of thermal electricity doesn't relate to the extent of carbon emissions in the second stage.

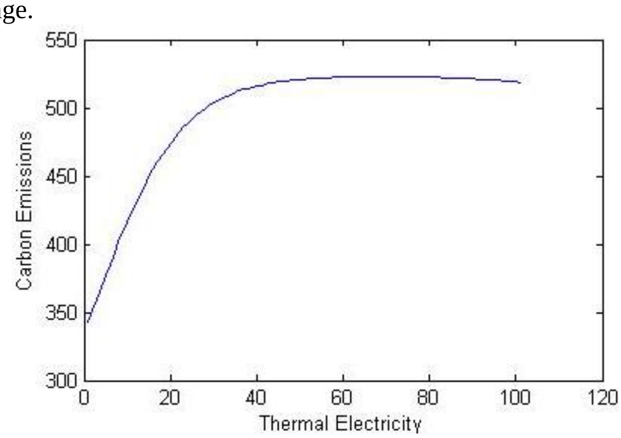

Fig. 4: The relationship between thermal electricity and carbon emissions.

As shown in Fig. 5, this study demonstrates that there is a negative relationship between renewable electricity and carbon emissions. It means that renewable electricity negatively influences carbon emissions. Because renewable energy is inexhaustible, the advantage of renewable electricity is that it can cause less impact on the environment. Thus, renewable electricity generation can replace electricity generation from fossil feuls to reduce carbon emissions. As a result, most countries encourage the development of renewable electricity to eliminate carbon emissions.

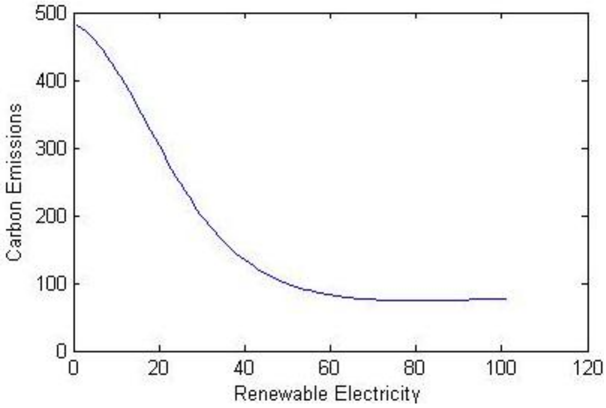

Fig. 5: The relationship between renewable electricity and carbon emissions.

Conclusions and implications:

This study focuses on the influences of natural gas consumption, thermal electricity, and renewable electricity on carbon emissions by using artificial neural network. Besides, this research would like to discuss the nonlinear relationships between carbon emissions and its three determinants - natural gas consumption, thermal electricity, and renewable electricity in in OECD. The data of the dependent variable and independent variables gathered from the Energy Information Administration (EIA) database. This paper collects the data of 32 countries in OECD in the period 1993-2010 and the sample contains 576 panel data which includes 461 training data and 115 testing data. The results show that natural gas consumption has an inverse U-shaped influence on carbon emissions. This study finds out that there are three stages in the relationship between natural gas consumption and carbon emissions. Natural gas consumption positively influences carbon emissions in the first stage. However, there is no relationship between natural gas consumption and carbon emissions. In the third stage, natural gas consumption negatively relates to carbon emissions. Since carbon emissions of natural gas are less than those of other fossil fuels, natural gas power plants can be used to replace other kinds of power plants to decrease carbon emissions in the third stage.

This study demonstrates that thermal electricity positively affects carbon emissions. The major source of thermal electricity comes from the burning of fossil fuels. Burning fossil fuels cause air pollution and increase carbon emissions which are directly related with the greenhouse effect. According to International Energy Agency (IEA), thermal electricity is the most popular electricity used in the world today. 40% of thermal electricity is produced through the burning of coal in 2008 (Lafrancois, 2012). By 2035, it should go down to approximately 37% (Lafrancois, 2012). Coal is currently the major source of thermal electricity which accounts for the main source of carbon emissions (Ghash *et al*., 2012). In order to reduce carbon emissions effectively, we need to decrease thermal electricity and develop more clean and environmental energy to replace thermal electricity.

In this study, we also find out that renewable electricity negatively affects carbon emissions. Since renewable energy comes from resources which are continually replenished, the benefit of renewable electricity is that it can cause fewer carbon emissions. Hence, renewable electricity generation can substitute for electricity generation from fossil feuls to decrease carbon emissions. This is the reason why there is a negative relationship between renewable electricity and carbon emissions. In 2011, Renewable electricity accounts for about 19% of all electricity (REN21, 2013). Global demand for renewable energy continues to increase in 2012, despite the international financial crisis, environmental policy uncertainty, and declining support in renewable energy markets (REN21, 2013). Total renewable power capacity worldwide exceeded 1,470 GW in 2012, and its growth rate is 8.5% in 2012 (REN21, 2013). Renewable energy and nuclear power are the world's fastest-growing energy sources in 2012 (EIA, 2013). However, the nuclear disaster in Japan caused by the earthquake on March 11, 2011 causes a massive panic for nuclear power in the world. Consequently, most countries encourage the development of renewable energy to substitute for nuclear and fossil fuel power in order to reduce carbon emissions. Besides the reduction of carbon emissions, the other advantage of renewable energy is the less risk of price fluctuation, comparing to the risk of price fluctuation of fossil fuels (Moore *et al*., 2010). Hence, renewable electricity is a better power alternative for industries and families in the world. Government has to formulate policies and incentives to support the development of renewable energy and to stimulate the research of technologies about renewable energy.

This research is conducted in OECD. Future research can focus on other areas or other countries to explore the relevant topics, and compare to this study. Moreover, this study explores the relationships between carbon emissions and its three determinants – natural gas consumption, thermal electricity and renewable electricity. Future research can focus on other determinants to explore the relevant topics, and compare to this study. In addition, this research discusses the nonlinear influences of natural gas consumption, thermal electricity and renewable electricity on carbon emissions by means of ANN. Future research can focus on other statistical methods to explore the relevant topics, and compare to this study. Finally, this study hopes that the research results can be useful for practitioners, researchers, and policy makers, and contribute to relevant and future research as reference.

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