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## IS IT POSSIBLE TO APPLY A DEEP LEARNING ALGORITHM TO INNOVATION MANAGEMENT RESEARCH?\*

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### Abstract

This paper aims to apply a deep learning algorithm to estimate the prediction of various external financial input variables on the adoption of eco-innovation practices such as renewable energy operations by 5456 SMEs. A Long Short-Term Memory Units (LSTM) is utilized to the data set to assess the performance of different input variables on the adoption of renewable energy. Furthermore, we process the dataset with different machine learning algorithms and compare the results. The findings indicate that LSTM gives the highest performance for all metrics. As a result, some essential theoretical implications for management scholars are given.

**Keywords:** *Artificial Intelligence, Machine Learning, Deep Learning, LSTM, Eco-innovation, Renewable Energy.*

## İNOVASYON YÖNETİMİ ARAŞTIRMALARINA DERİN ÖĞRENME ALGORİTMASI UYGULAMAK MÜMKÜN MÜ?

### Öz

Bu makale, farklı dış finansman faktörlerinin KOBİ'lerin yenilenebilir enerji gibi eko-inovasyon uygulamalarını benimsemesini nasıl etkilediğini açıklamayı amaçlamaktadır. Derin öğrenme algoritması uygulanarak 5456 KOBİ'nin yenilenebilir enerji operasyonlarını benimseme konusunda çeşitli dış finansal girdi değişkenlerinin tahmini incelenmiştir. Yenilenebilir enerjinin benimsenmesine ilişkin farklı girdi değişkenlerinin performansını değerlendirmek için veri kümesine Uzun Kısa Süreli Bellek Modeli (LSTM) uygulanmıştır. Ayrıca veri setini farklı makine öğrenme algoritmaları ile karşılaştırılmıştır. Bulgular, LSTM'nin tüm metrikler için en yüksek performansı verdiğini göstermektedir. Sonuç olarak, bazı önemli teorik çıkarımlar verilmiştir.

**Anahtar kelimeler:** *Yapay Zekâ, Makine Öğrenmesi, Derin Öğrenme, LSTM, Eko-inovasyon, Yenilenebilir Enerji.*

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## **1. INTRODUCTION**

Artificial Intelligence (AI) describes the ability of machines to execute tasks that would usually necessitate human intellect, such as graphical perception, language recognition, and reasoning. In addition, it enables machines to learn from past experiences and adapt to new stimuli (Chalmers et al., 2021). Most current Artificial Intelligence (AI) tools employ big data analytics and advanced technologies such as machine learning (ML), deep learning (DL), and artificial neural networks (ANNs) (Obschonka and Audretsch, 2020).

Few studies have recently applied deep learning in various settings, such as multi-band microstrip antennas (Özkaya et al., 2021) or Parkinson's disease with sentiment analysis (Çevik and Kilimci, 2021). This transformative potential of AI has also created great interest among the business community and innovation management scholars. AI is already reshaping entrepreneurial businesses and the corresponding research studies (Lévesque et al., 2020). Innovation management research aims to develop a more advanced theoretical framework and make real-world applications of it (Wiklund, 2019). AI technology can help researchers (Lévesque et al., 2020) come up with new ways to think about many interesting social and economic areas. However, there is a clear gap in state-of-the-art research on how AI can be effectively applied in innovation management research (Obschonka and Audretsch, 2020).

In this article, we apply and evaluate a deep learning approach, especially a Long Short-Term Memory Units (LSTM), to the data set to evaluate the performance of different input variables on the adoption of renewable energy. Furthermore, we evaluate the dataset with different machine learning algorithms and compare the results.

The rest of the paper is structured as follows: Section 2 describes the dataset and the methodical approach of this study. Section 3 discusses the application and analysis of the deep learning model. Section 4 offers conclusions and a discussion of the management and policy implications of the study.

## **2. RELATED LITERATURE REVIEW**

SMEs cause a significant proportion of a country's total pollution and are responsible for significant adverse environmental impacts (Parker et al., 2009; Yacob et al., 2019), bringing SMEs to the attention of experts and governments (Gadenne et al., 2009). These organizations help SMEs reduce their environmental footprint by implementing rules, initiatives, and tools (Yacob et al., 2019). Many small businesses perceive environmental regulations as more burdens than larger businesses. However, SMEs have characteristics that could enhance their commitment to greener activities (Hoogendoorn, 2015). For example, the flexibility of SMEs enables them to produce environmentally friendly goods and services (Pekanov Starevi et al., 2017). This directly results from increased public awareness of limited resources, waste production, and other environmental impacts (Moric et al., 2022). Therefore, the private sector has been pushed to explore resource-efficient eco-innovations.

Eco-innovation as a specific form of innovation was first mentioned in the literature in the 1990s (Fikirli et al., 2022; Kemp and Oltra, 2011). The term "eco-innovation" was coined by Claude Fusler and Peter James in 1996. They defined it as novel processes and products that enhance benefit to consumers and companies while significantly reducing ecological impacts (Roddis, 2018). Also, Kemp and Pearson (2007) describe eco-innovation as the creation, appropriation, or use of novel goods, service, manufacturing process, or business or management system that decreases ecological risks, pollution, and other harmful effects of resource usage (containing energy consumption) during its lifespan related to practical alternatives. Andersen (2008) identifies eco-innovation as novelties competent for achieving green rents in the marketplace from an industrial dynamics perspective. The notion is directly associated with competitiveness and does not discuss the green issues of specific developments. The emphasis of eco-innovation investigation should be on how ecological concerns are incorporated into economic activity (Schiederig et al., 2012). Arundel and Kemp (2009) argue that eco-innovation is a different idea of enormous relevance to businesses and policymakers. It involves developing technologies with less green effect than comparable options. These can be technical or non-technical (marketing, institutional, or organizational) advances. Economic or environmental factors can drive eco-innovation. The former includes goals such as resource reduction, waste management expenses, pollution control, and the selling of eco-friendly goods on the world market (Schiederig et al., 2012). Although many researchers have defined eco-innovation differently (Charter and Clark, 2007; Oltra and Saint Jean, 2009; Fikirli et al., 2022), all definitions incorporate

environmental aspects and focus on the two major benefits of eco-innovation: reduced negative impacts on nature and increased efficiency in managing available resources (Hojnik and Ruzzier, 2016).

Rexhauser and Rammer (2014) make a distinction between prescribed and voluntary eco-innovation. Eco-innovation is mandated and increases the productivity of a firm's resources and has a stronger impact on profitability than voluntary eco-innovation (Horbach, 2018). Manufacturers that choose the non-green path face higher costs due to tax penalties, pollution permits, and other fees imposed by regulators (Pekanov Starevi et al., 2017). Franco and Marin (2017) calculated the direct environmental impacts of taxes and the indirect environmental impacts of innovation on upstream and downstream partners in the supply chain. They found that downstream directives can lead to new goods and services and new markets, but upstream directives can hinder innovation and productivity. Because new production techniques and technologies must first be created and modified to meet additional criteria, the price of green production today is higher than that of traditional production (Pekanov Starevi et al., 2017). Regardless of the cost, customers who want to buy environmentally friendly products or services bear this expense (Ambec and Lanoie, 2008). Today, companies that focus on cost leadership use more eco-innovation tools than those that do not (Delmas and Pekovic, 2015). The willingness of customers to bear the costs of eco-innovation measures could influence the company's decision-making process (Horbach, 2008; Hoogendoorn, 2015). Using eco-friendly techniques, methods, and strategies depends on the environmental awareness, ecological consciousness, and development level of SMEs, as well as the company's advantages (Pekanov Starevi et al., 2017). Intense competition and rising energy prices have accelerated the adoption of green techniques (Kabiraj et al., 2010). One advantage of eco-innovations is their lower manufacturing costs due to their more efficient energy use (Olson, 2013). Ecological aspects affect a company's expenses, revenues, and business results (Molina-Azorin et al., 2009). However, according to a patent analysis conducted by Marin and Lotti (2017), the value of eco-innovations is lower than that of other forms of inventions and is mainly obtained by polluting companies with high compliance costs. Hottenrott et al. (2016) studied the impact of green technologies and organizational change and found that only green technologies associated with organizational change lead to consistent or high productivity.

## 2. DATA AND METHODOLOGY

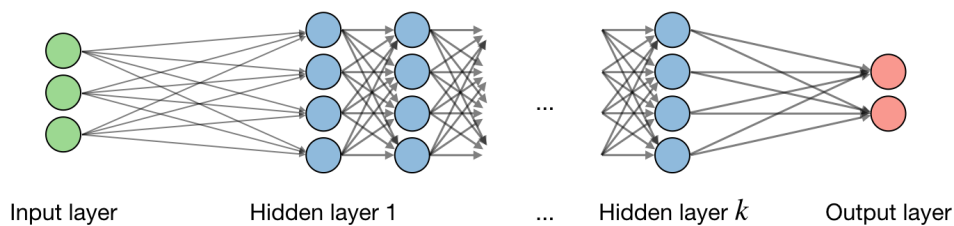
We use information from the European Union's Flash Eurobarometer 441 (European Commission, 2016) study, which surveyed 5873 SMEs in Europe about how they use green initiatives and what kinds of outside funding they use to help them use eco-innovation practices like using renewable energy (Table 1). Several AI methods are applied to the dataset.

**Table 1: Variables**

Name	Type	Unit
<b>Input</b>		
Green loan	Binary	Coded into 0 and 1
Standard bank loan	Binary	Coded into 0 and 1
Government grant	Binary	Coded into 0 and 1
EU related funds	Binary	Coded into 0 and 1
Green banks or other private institutions stimulate	Binary	Coded into 0 and 1
Crowdfunding	Binary	Coded into 0 and 1
Business Angels	Binary	Coded into 0 and 1
Peer-to-Peer lending	Binary	Coded into 0 and 1
Capital market	Binary	Coded into 0 and 1
Risk Capital/Venture Capital	Binary	Coded into 0 and 1
Turnover	Categorical	Coded into 1 and 8
Number of Employees	Categorical	Coded into 1 and 3
Age	Categorical	Coded into 1 and 3
Growth	Categorical	Coded into 1 and 7

R&D Intensity	Categorical	Coded into 1 and 5
Investment in resource efficiency	Categorical	Coded into 1 and 4
Products to companies or other organisations	Binary	Coded into 0 and 1
Products directly to consumers	Binary	Coded into 0 and 1
Services to companies or other organisations	Binary	Coded into 0 and 1
Services directly to consumers	Binary	Coded into 0 and 1
Available Information	Binary	Coded into 0 and 1
Awareness Financial Incentives	Binary	Coded into 0 and 1
Retail	Binary	Coded into 0 and 1
Manufacturing	Binary	Coded into 0 and 1
Industry	Binary	Coded into 0 and 1
Services	Binary	Coded into 0 and 1
28 Countries included in the sample	Binary	Coded into 0 and 1
<b>Output</b>		
Adoption Renewable Energy	Binary	Coded into 1 and 0

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two kinds of neural networks that are commonly used. ANNs are a class of models that are built with layers. The diagram in Fig. 1 depicts the terminology associated with ANN architectures (Amidi and Amidi, 2018):



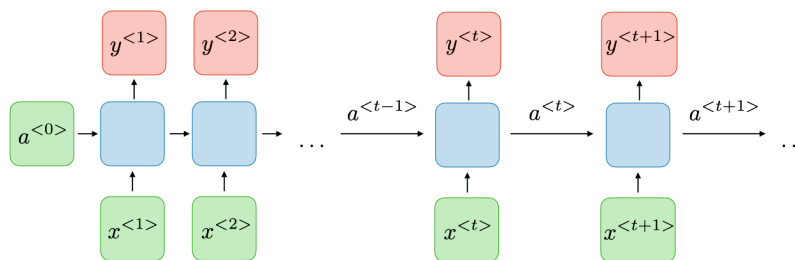
**Figure 1: Artificial neural network architecture (Amidi and Amidi, 2018)**

By mentioning  $i$  as the  $i^{th}$  network layer and  $j$  as the  $j^{th}$  network layer hidden unit, we have

$$z_j^{[i]} = b_j^{[i]} + w_j^{[i]T} x, \tag{1}$$

where  $z$ ,  $n$  and  $w$  denote the output, bias, and weight, respectively.

RNNs are a form of ANN that has hidden units and allows former outputs to be applied as inputs. In Fig. 2, the recurrent process of a standard RNN is given (Amidi and Amidi, 2019). The architecture of an RNN unit is given in Fig. 3 (Amidi and Amidi, 2019).



**Figure 2: The process of a RNN (Amidi and Amidi, 2019)**

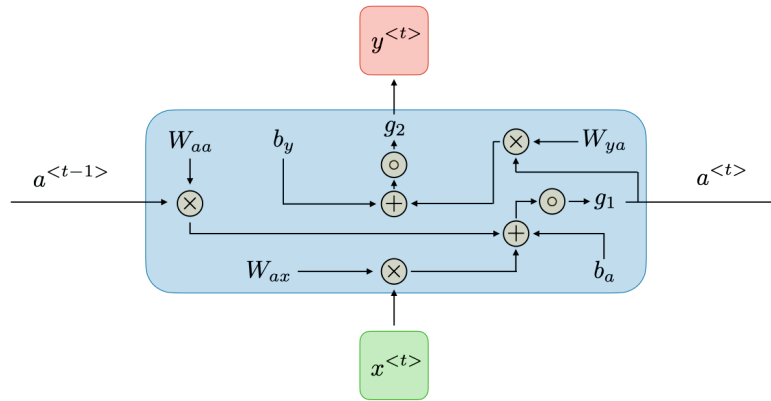


Figure 3: The architecture of an RNN (Amidi and Amidi, 2019)

Standard RNNs have a problem with vanishing gradients. Long Short-Term Memory Units (LSTM) solve this problem. In the LSTM structure, attributes that make sense of past and future information are moved recursively. Fig. 4 shows an LSTM structure. In this model, the activation function is used at three different points: input, recall/forget, and output. In the input and output layers, the hyperbolic tangent function is usually chosen, and in the remember/forget gates, the sigmoid function is used (Amidi and Amidi, 2019).

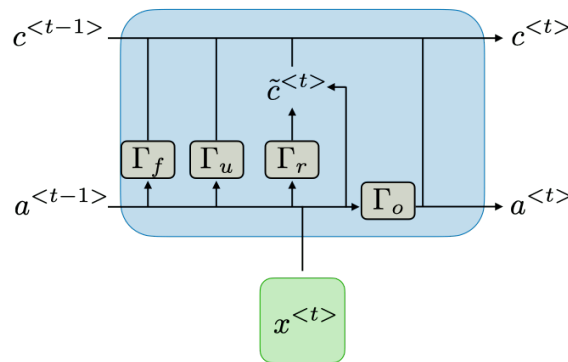


Figure 4: The architecture of a LSTM (Amidi and Amidi, 2019)

$\hat{c}^{(t)}$  symbolizes the candidate's value for memory. Hyperbolic tangent is used as the activation function. Here, the candidate value is calculated as

$$\hat{c}^{(t)} = \tanh(W_c[\Gamma_r * a^{(t-1)}, x^{(t)}] + b_c), \quad (2)$$

where \* is the element-wise multiplication of two vectors.

In addition, update and relevance gate values are calculated in the LSTM. For these values, the sigmoid is used as an activation function. The update gateway and the relevance gate are calculated as follows:

$$\Gamma_u = \sigma(W_u[a^{(t-1)}, x^{(t)}] + b_u), \quad (3)$$

$$\Gamma_r = \sigma(W_r[a^{(t-1)}, x^{(t)}] + b_r). \quad (4)$$

The most important difference of this structure from gated recurring units (GRU) is that the interest gate is specialized in the LSTM structure, obtained by two new equations as forget ( $\Gamma_f$ ) and output gate ( $\Gamma_o$ ). Thanks to the forget gate, the weight of information transferred from the past, but not necessary, is reduced. With the update pass, a more effective output is produced with the effect of forgetting (Hochreiter and Schmidhuber, 1997) as

$$\Gamma_f = \sigma(W_u[a^{(t-1)}, x^{(t)}] + b_f), \quad (5)$$

$$\Gamma_o = \sigma(W_r[a^{(t-1)}, x^{(t)}] + b_o). \quad (6)$$

Using (2), (3), and (5), the new  $\hat{c}^{(t)}$  value can be obtained as

$$c^{(t)} = \Gamma_u * \hat{c}^{(t)} + \Gamma_f * \hat{c}^{(t-1)}. \quad (7)$$

And, thus the new value of  $a^{(t)}$  can be obtained using (6) and (7) as follows:

$$a^{(t)} = \Gamma_o * c^{(t)}. \quad (8)$$

### 3. EXPERIMENTS AND RESULTS

The LSTM model is implemented using Python 3 programming language with the help of the Google Colabs tool, which supports the Tesla K80 GPU platform. TensorFlow and Keras Libraries were used as the basic library.

Binary cross entropy is used in the loss calculation. Cross-entropy loss serves to assess the performance of a classification model whose output has a probability value between 0 and 1. The further the estimated probability is from the original label, the greater the cross-entropy loss. The cross-entropy loss is widely used in deep learning and is defined as follows:

$$L(z, y) = -[y \log(z) + (1 - y) \log(1 - z)]. \quad (9)$$

Accuracy, precision, recall and F1-score metrics were computed to estimate the results. Calculations of these metrics can be shown as

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (10)$$

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

$$Recall = \frac{TP}{TP + FN} \quad (12)$$

$$F1 - Score = 2 * \left( \frac{Recall * Precision}{Recall + Precision} \right). \quad (13)$$

A summary of the designed network is given in Table 2.

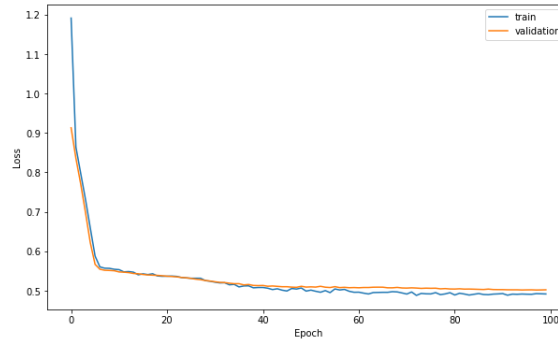
**Table 2: Summary of the designed LSTM model**

Layer	Layer Type	Unit	Parameters
1	LSTM	1	224
2	Dropout	1	0
3	LSTM	50	10400
4	Dropout	50	0
5	LSTM	50	20200
6	Dropout	50	0
7	Dense	1	51

The obtained results are summarized in Table 2. The training and test subduction-iteration graph for LSTM was obtained as in Fig. 5. In addition, in order to measure the performance of LSTM, mean absolute error (MAE),

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - y_i^*|, \quad (14)$$

with the environment between the training data and the estimation calculated at the LSTM output is also measured and presented in Table 3.



**Figure 5: LSTM model loss for training and validation sets**

**Table 3: The results achieved by LSTM model**

Metric	Result
MAE	1.2
Accuracy	%90
Precision	%89
Recall	%89
F1-Score	%89

In order to measure how successful the solution obtained with LSTM is, the same dataset is processed with different learning algorithms, and the obtained results have been compared. In this study, Decision Tree Regression, Random Forest, AdaBoost, Bagging, Logistic Regression, and Support Vector Machine were used for comparison. Table 4 shows that the LSTM method outperforms conventional methods.

**Table 4: Results obtained by conventional methods**

Model	MAE	Accuracy
Decision Tree	0.18	81.2%
Random Forest	0.23	76.6%
AdaBoost	0.25	74.6%
Bagging	0.25	74.6%
Logistic Regression	0.16	83.7%
SVM	0.16	82.7%

#### **4. DISCUSSION AND CONCLUSION**

The study of eco-innovation is still in its early stages, but recent years have shown a growing interest in the subject among policymakers, researchers, and practitioners. As environmental challenges become more pressing, eco-innovation policies continue to spark interest in the scientific community. The findings of this analysis have implications for governments, businesses, and scientific researchers.

From a scientific standpoint, this study enhances the literature by demonstrating that deep learning algorithms can usher in a new era in conducting research analysis in innovation management. This work explores the access to different types of external funding and factors used by European SMEs to invest in renewable energy and how this approach finally influences their implementation of renewable energy practices through applying a deep learning algorithm. The role of external financial factors in renewable energy adoption can be highlighted by testing and building new theories. Comparing the obtained results (Tables 3 and 4), it can be seen that the LSTM algorithm performs the highest for all metrics. The paper is characterized by the fact that the research results show that Deep Learning, especially LSTM, can be used in innovation management research and can potentially change the way innovation management research projects are conducted.

Numerous scholarly contributions have used various empirical methods to challenge theories and practices related to eco-innovation. The vast majority of studies we examined for this literature review use quantitative research methods and attention on the level of eco-innovation known as diffusion. (Hojnik and Ruzzier, 2016) Yücel and Terzioğlu (2023), for example, used a dynamic spatial panel data approach to show eco-innovation capacities in Turkey and European countries in the context of sustainable development based on 2010–2018. Fikirlı et al. (2022) assessed the level of eco-innovation efficiency in Turkey and analyzed the country's eco-innovation index. Aguilera-Caracuel and Ortiz-de-Mandojana (2013) used an institutional approach and a pairwise analysis of innovative and non-innovative green firms to discover that innovative green firms are located in settings with stricter environmental regulations and higher environmental standards. Daz-Garcia et al. (2015) reviewed previous research and provided an outline of the current literature on eco-innovation, identified the most appropriate publications in the area, and discussed the subjects of importance to the reader.

However, traditional quantitative methods cannot still deal with incomplete data collection. Horbach (2014) specified insufficient data in the empirical literature to analyze the determining factor of eco-innovation. Therefore, this study adds to the innovation management literature and expands our understanding of the potential application of the AI method in scientific innovation management research.

There is a discrepancy between the expectations of innovation management journals regarding new theoretical approaches and the research conducted by scholars in this area. This discrepancy can also be observed in innovation management research, which works hard to achieve and maintain its research relevance (Lévesque et al., 2020). In our study, we used a large data set. Therefore, a researcher needs to understand the context in which the Big Data was generated. Complex modeling needs to be partitioned to test the hypothesis. Due to the complexity of the different data sources, this is a challenging process (Townsend and Hunt, 2019).

Another problem is the black-box models used by AI algorithms for prediction (Tonidandel et al., 2018). For example, although artificial neural networks (ANNs) have shown exceptional performance in prediction, the actual architecture of ANNs, which consists of nodes and layers and their weight distributions for predictors, remains puzzling to management scientists (Tonidandel et al., 2018). Another major problem is management scientists' lack of AI skills to apply better data analysis techniques professionally.

However, our findings show that AI can be used in innovation management research by testing existing theories and developing new theories to address emerging difficulties and open questions (Obschonka and Audretsch, 2020). Consequently, innovation management researchers and AI scholars must collaborate to explore what might work in principle and test it to develop a new analytical discipline (Lévesque et al., 2020).

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