Leveraging Transdisciplinary Engineering in a Changing and Connected World
P. Koomsap et al. (Eds.)

doi:10.3233/ATDE230675

Towards Creativity Measurement in the Energy Industry

Zhao ZHANG[a,1], R. Chadwick HOLMES[a] and Victor TANG[b]
[a] *Chevron Technical Center, a division of Chevron U.S.A. Inc., Houston, TX, 77002, USA*
[b] *Massachusetts Institute of Technology*

Abstract. Creativity plays a critical role in how companies manage and strategically reposition during periods of change, including the current digital transformation and energy transition in the energy industry. However, a holistic framework is absent to systematically exploit ideas, evaluate and prioritize competing ideas with limited resources, and turn ideas into valuable and marketable products. Thus, companies need to be able to measure their creative ideas so that resources and R&D investments are far more effective. We implemented a new matrix-algebraic framework called Quantitative Creativity Scores (QCS) to evaluate innovative ideas and identify areas we need to improve to stay competitive. Specifically, we adapted the feature-attribute creativity matrices to represent innovative ideas. We then applied the idea operators, which use matrix-expressed ideas as operands, to calculate the quantitative creativity scores. Significant research has been conducted in salt body detection from seismic data, a vital task in hydrocarbon exploration and storage detection of new energy vectors like hydrogen. There has been a significant amount of research conducted in this area, making it a challenging topic for innovative research and development. We applied this QCS evaluation framework to evaluate two real-world novel salt-body detection workflows. Through this assessment, we can compare, evaluate, and quantitatively calculate which idea has the most potential for success and leverage the existing knowledge to drive further innovation. Our results demonstrate that this approach allows us to generate and evaluate new ideas in a repeatable and reproducible way, which can help us to identify and pursue creative ideas to exploit their market potential fully.

Keywords. Creativity; creativity management; creativity and novelty measurement; matrix-algebraic method.

Introduction

The energy industry has experienced significant transformations in recent years driven by technological advancement, environmental regulations, and changing consumer preferences. Energy companies must explore new ways to identify, generate, distribute, and consume energy, reduce their carbon footprint, and improve energy efficiency. In this context, the ability to continue innovating and become ever more adaptable to new challenges is essential for a company to thrive and remain competitive in the long run. However, innovation is a complex process that is spearheaded by creativity with commercialization of the innovative product as the end goal. As illustrated in Figure 1, the innovation process involves a series of steps where a creative idea is generated,

[1] Corresponding Author, Mail: zhaoz@mit.edu.

evaluated, and developed into an invention or prototype. The final step involves successfully implementing the invention into a commercialized innovation and bringing it to market. Thus, creativity is a fundamental prerequisite for driving innovation, which can lead to new business opportunities and growth.

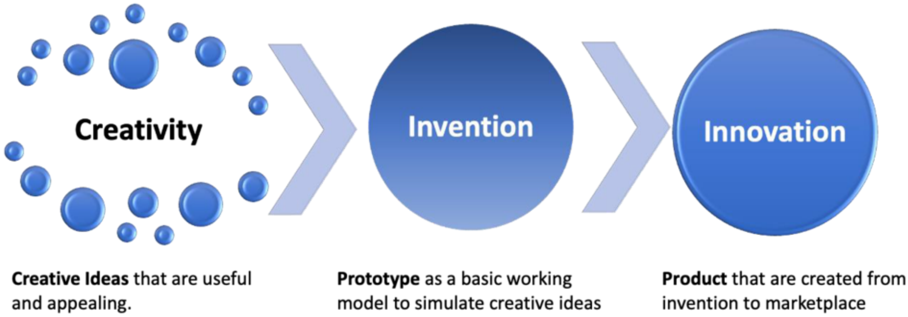

Figure 1. Steps in the process of Innovation.

An egg does not guarantee a chicken. Creativity does not always guarantee successful innovation. Firms should not conflate creativity and innovation in their evaluation of their standard practices, industry patterns, and shared beliefs. Creativity requires mental acuity and discernment to think about existing practices, patterns, and beliefs to develop fresh and original ideas [11]. While numerous theories and practices exist related to measuring innovation [10][17], there has been comparatively less emphasis on the development of methods for measuring creativity. Given the assumption that all creative ideas can be implemented to equally increase profit and strengthen competitive advantage, current research emphasizes the mechanics of generating novel and innovative ideas [2][4][6][7]. Qualitative narratives remain the dominant criteria for ranking and selecting creative ideas [11].

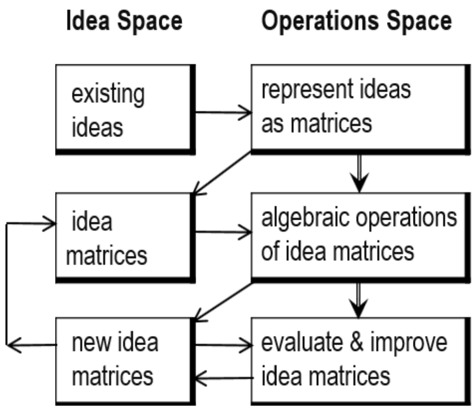

Figure 2. Framework of idea matrix representation and generative analysis (adapted from [11]).

Despite the importance of systematically exploiting ideas, evaluating, and prioritizing competing ideas, with the goal of transforming them into marketable products, a comprehensive framework remains to be developed to achieve this. How can we represent existing ideas as *operands* for inventive and generative manipulations, and then *operationalize* ideas as operands? We propose the following approach:

- *represent* the ideas using a consistent and completely general specification schema,
- *use* these *representations* to systematically *generate* potentially new creative ideas,
- *evaluate* and *rank* competing ideas rigorously and quantitatively,
- *analyze* and *improve* ideas in a repeatable way.

There needs to be more analytical representational schema and quantitative methods for assessing and analyzing creativity rigorously. In this paper, we applied a novel matrix-algebraic framework called Quantitative Creativity Scores (QCS) as shown in Figure 2 [11]. We begin with the concept of creativity as in the literature, *viz.* simultaneity of novelty and usefulness. We then describe a new schema to represent an idea as an attribute-feature matrix and constituent measurement units, in ratio scales [8][13] of novelty and usefulness. Mathematics informs and motivates our approach of using matrices to express ideas and to manipulate, evaluate, and improve ideas. We introduce our examples to illustrate how they can be used. We conclude with a summary, remarks on validity, and directions for follow-up work.

1. Methodology

We begin by discussing how to analytically specify a creative idea. A creative idea is one that is *simultaneously* novel and useful [3][14][16][18][19]. Sternberg and Lubart [19] define creativity as a *capability* to "produce work that is both *novel* (i.e., original, unexpected) and appropriate (i.e., *useful,* adaptive concerning task constraints)". Similarly, Houtz and Patricola [3] describe creativity "as a process which leads to the production of something that is both *novel* and *useful*".

Creativity begins with ideas. We present a matrix specification process as an original way to define an idea. We also present matrix operations to algebraically manipulate ideas, and, to explore, evaluate, rank, and improve them against competing ideas. Our intent is to offer operational tools, targeted at individuals, to stimulate and improve creative ideas about artifacts.

A novel idea is new, original, unexpected, and surprising [5]. Novelty is subjective to the experience and temporal context of the observer [21]. A useful idea is endowed with utility, appropriateness, and social value [19]. Although creativity is a personal ability, novelty and usefulness are judged socially in a temporal context. Regrettably, some magnificently creative ideas are so unique that they are rejected or ignored as irrelevant or so radical and disruptive they are dismissed. Rejection does not mean an idea has no merit.

Table 1. Definition of intensity measures [13].

Intensity	Definition	Explanation	Intensity	Definition	Explanation
0	none	barely perceptible	7	strong	readily perceptible
1	weak	perceptible	9	very strong	high contrast perceptible
3	moderate	not weak nor strong	10	dominant	dominant
5	average		2,4,6,8	intermediate	values

Creativity is the result of sustained effort, deliberate and actionable activities. To conceive an idea requires domain knowledge, conceptualization skills, and motivation [1][21]. Without creativity-relevant skills to productively generate and manipulate ideas, knowledge and motivation will remain unfulfilled as assets for new ideas [15].

Therefore, it is necessary and sufficient that these three properties – simultaneity, novelty, and usefulness, be specified unambiguously. To meet these three conditions, we propose a **novelty matrix**, a **usefulness matrix**, and a **creativity matrix** that is the multiplicative product of the novelty and usefulness matrices. If either novelty or usefulness is zero, the product is zero and there is no creativity. This reduces *conflation* and *ambiguity* at the specification level, as well as the conceptual level. We will present the matrix constructs, illustrate their use, and discuss the insights that the process uncovers.

1.1 Novelty, Usefulness, and Creativity Matrices

We represent novelty using a $p \times q$ **novelty matrix** N_{pq}. The columns of N_{pq} are its *features* in domain-specific terms. The rows are the domain-specific *attributes.* Each entry of the matrix has a value that associates the attributes' **novelty-intensity** with features. The **usefulness matrix** U_{pq} is similarly defined with feature-columns and attribute-rows. This is consistent with our definition of feature and attribute.

Given an idea novelty matrix N_{pq}. Consider column ***i*** and row ***j***, representing feature ***i*** and attribute ***j***, respectively. Matrix entry $\boldsymbol{n_{ij}}$ represents the intensity of attribute ***j*** in feature ***i***. How is the intensity expressed? We use a 10-point scale as shown in Table 1 above. For example, if the attribute is readily perceptible, score with a number 7.

1.2 Idea Manipulation

We can use these matrices to analyze the creativity scores of an $C^{xyz}{}_{mn}$ product that is expressed by matrices $U^{ixyz}{}_{mn}$ and $N^{ixyz}{}_{mn}$ norm. We use the Euclidean norm, also called Hilbert-Schmidt, or Frobenius norm, defined as,

$$\| C^{xyz}{}_{mn} \| = \sqrt{\textstyle\sum_{\mathbf{m}}\sum_{\mathbf{n}} a^2{}_{mn}} \tag{1}$$

A matrix's norm is its "amplifying power" [12], thus we define the norm of an idea's novelty-matrix as its *novelty-metric.* And we define the norm of a usefulness-matrix as its *usefulness-metric*. The creativity is the **multiplicative** measure of novelty and usefulness. Given the simultaneity property of creativity, the product of the novelty and usefulness metrics is appropriate as a *creativity metric.* We define the **creativity matrix** $C^{xyz}{}_{mn}$ by the Hadamard product of $U^{ixyz}{}_{mn}$ and $N^{ixyz}{}_{mn},$

$$C^{xyz}{}_{mn} = U^{ixyz}{}_{mn} \circ N^{ixyz}{}_{mn} \tag{2}$$

The Hadamard form is used for convenience since the matrices may not be square. We can use these norms to compare the novelty, usefulness, and creativity of an idea. Our matrix and operators are targeted at individuals to explore, test, refine and improve ideas. For an individual, these tasks are straight forward, simply apply personal and professional judgement. But where the socio-technical goal of consensus is desirable, the same thinking can be used with small or large groups.

2. Application and discussion

Within this section, we will utilize the QCS framework to assess and prioritize two creative proposals within the energy sector. Identifying and mapping salt formations is essential in hydrocarbon exploration and energy storage detection. The presence of salt bodies can significantly impact the location and distribution of hydrocarbon reserves and influence the safety and efficiency of operations. Furthermore, salt bodies can serve as potential reservoirs for hydrogen storage, making their detection and characterization critical for developing hydrogen as a new energy vector. Despite the significant research in this area, salt body detection remains a challenging topic for innovative research and development. Researchers continue to develop new algorithms and techniques for identifying and characterizing salt bodies in seismic data to improve the accuracy and reliability of exploration and storage operations.

Due to limited resources, companies need to select a fraction of the ideas to actively prototype and develop based on their capacity at any given moment. In this context, we have identified two distinct workflows from the literature that have the potential for further development. These are 1) A salt body detection approach that employs Gray-level co-occurrence Matrix (GLCM) based techniques, and 2) A detection model that utilizes Convolutional Neural Network (CNN) based methods. Both workflows are machine learning-based and involve various stages such as feature extraction, model training and validation, model deployment, and salt body prediction. While GLCM relies on statistical techniques to extract limited texture features, CNN employs a complex graphical model that can automatically generate, learn, and classify features. We are going to apply the QCS evaluation framework to evaluate these two real-world novel salt-body detection workflows.

2.1 Idea Matrix for Salt-body Detection

We first represent the salt-body detection workflow as a feature-attribute matrix. The selection of features and attributes is critical to accurately describe novelty, usefulness, and creativity of an idea. It should be noted that novelty and usefulness are not treated as single, indivisible factors, but rather as distinct collections of basic variables. Creativity is not simply the product of two monolithic lumps, but the causal relationships between elemental *attribute* variables and *feature* variables determined by working principles and mechanisms, rather than subjective opinions. The relationships between features and attributes are not mere correlations. Thus, the first step to decomposing the salt-body detection workflow into the feature-attributes matrix is establishing the working principles and understanding the mechanisms.

Table 2. Matrix representation - attributes selection criteria.

Selection Categories	Selected Attributes
User Experience	Easy input data collection; Workflow ease of use; Intuitive interpretations of predicted results; UI complexity;
Workflow Performance	Model Accuracy; Efficient computation; Efficient HPC usage;
Development Complexity	Integration with existing platform; Project developing time; Maintenance and upgrade costs

A well-designed workflow enables users to navigate through an application seamlessly, completing tasks with minimal effort and maximizing productivity. Workflow performance is a crucial factor to consider when evaluating a salt-body detection workflow, as it determines how quickly and accurately a user can complete the salt-body interpretation task. When it comes to application development, user experience is an essential factor that cannot be overlooked. A good UX design enables an application that functions properly and provides a seamless and intuitive user experience. From the developer's perspective, development complexity is another vital aspect, particularly if the firm has limited resources and an urgent deadline to deliver the product to the end customers. The management team needs to assess the development process's complexity and ensure they have the necessary resources to complete the project within the given timeframe. Thus, the primary attributes are derived based on key elements that impact user experience, workflow efficiency, and development complexity. We have chosen ten attributes that fall into these three categories as shown in Table 2.

The salt-body detection workflow based on machine learning comprises three main steps: model training, inference, and visualization. The first step, model training, involves feeding the machine learning algorithm with data to learn and extract features that distinguish salt bodies from other geological features. The second step, inference, is where the trained model is applied to new data to predict the location of salt bodies. Finally, the third step, visualization, involves presenting the results of the model in a clear and understandable format, such as a 2D or 3D visualization of the geological structures. By following these three steps, as shown in Table 3, we selected seven features to evaluate a machine learning based salt-body detection workflow.

Table 3. Matrix representation - features selection criteria.

Workflow Mechanism	Selected Features
Model Training	Acquisition of geological structure data; Training data for machine learning; Supervised machine learning; Validation using blind test data.
Inference	Inference data preparation; Predict salt-body boundary on inference data
Visualization	Producing a 3D visual model

Therefore, the two proposed salt-body detection ideas can be represented by matrices. Rows of the matrices are the selected 10 domain specific attributes (Table 2), and columns of the matrices are the selected seven features (Table 3). For the salt body detection approach that employs GLCM based techniques, the creativity matrix $C^{GLCM}{}_{10,7}$ is the Hadamard product of the usefulness matrix $U^{GLCM}{}_{10,7}$ and the novelty matrix $N^{GLCM}{}_{10,7}$. For the CNN approach, the creativity matrix $C^{CNN}{}_{10,7}$ is calculated from the usefulness matrix $U^{CNN}{}_{10,7}$ and the novelty matrix $N^{CNN}{}_{10,7}$.

2.2 Matrix Operation

Mathematics, where operators and operands are always rigorously defined, allows us to better understand how to represent ideas quantitatively and enables us to think of ideas as operationalizable spaces. After we define the salt-body detection workflow as a feature-attribute matrix, we can leverage matrix algebra to operate and analyze two different salt-body detection ideas. Our goal is to rank these two competing ideas in terms of creativity and to improve the most creative idea.

Figure 3 illustrates the novelty $N^{GLCM}{}_{10,7}$ and usefulness matrices $U^{GLCM}{}_{10,7}$ of the salt-body detection workflow via GLCM approach. Each entry of the matrix $U^{GLCM}{}_{10,7}$ is a measure of the attributes' usefulness-intensity. Matrix cell $U^{GLCM}{}_{i,j}$ represents the intensity of attribute i in feature j, which is expressed using a 10- point ratio scale listed in Table 1. The novelty matrix is similarly defined. By applying the same mechanics, we can depict the salt-body detection workflow using CNN through novelty and usefulness matrices, as illustrated in Figure 4.

Both workflows utilize seismic data that contain rich geological structure information, resulting in comparable levels of novelty and usefulness scores for both workflows at training and inference data preparation stages. The GLCM approach is based on the traditional machine learning algorithm (e.g., random forest, XGBoost), where users need first calculate GLCM attributes and manually select and extract other texture features for the training stage. CNNs are powerful tools for automatically extracting texture features from images and have many applications in computer vision and image analysis. It typically consists of multiple layers, each performing a specific function in the feature extraction process. This architecture allows the CNN network to learn discriminative features directly from the input data, resulting in improved prediction accuracy compared to traditional machine learning algorithms. Additionally, CNNs can capture spatial dependencies and patterns in the image data, making them particularly effective for salt-body recognition and segmentation tasks. Thus, at the training data pre-processing and supervised machine learning training and inference stages, the CNN workflow shows higher novelty and usefulness scores on model performance attributes.

Salt-body detection via GLCM	Novelty Matrix							Usefulness Matrix						
	Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model	Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model
Easy input data collection	2	0	0	2	2	0	0	4	0	0	4	4	0	0
Workflow ease of use	2	0	4	3	2	4	2	6	0	5	6	6	8	8
Model accuracy	0	0	5	3	0	5	0	0	0	5	4	0	4	0
Efficiency computations	2	5	5	3	2	3	2	8	4	5	5	8	5	8
Efficient HPC usage	2	2	4	3	2	3	2	8	4	4	5	8	4	8
Intuitive interpretations of predicted results	0	0	0	3	0	5	0	0	0	0	5	0	5	0
UI complexity	2	0	0	3	2	0	2	6	0	0	6	8	0	6
Integration with existing platforms	2	2	4	4	2	4	2	8	5	3	3	8	3	4
Project developing time	2	4	5	4	2	5	2	7	3	3	4	8	4	7
Maintenance and upgrade costs	2	3	5	4	2	5	2	7	3	3	4	8	6	6

Figure 3. Idea matrix of salt-body detection via GLCM.

However, training and inference of CNN models require significant computational resources, typically provided by High-Performance Computing (HPC) systems. HPC access can be a challenge for integrating CNNs into existing commercial platforms, as they need access to HPC resources or an HPC API. Transferring data between an HPC system and a local server can be challenging, as it often involves moving large amounts of data across different networks and file systems. To facilitate this process, developers must build additional workflows to automate data transfer and synchronization between the HPC and local servers, which can be a time-consuming and error-prone process. The CNN workflow is therefore judged with high scores in the novelty matrix but low scores in the usefulness matrix for development complexity attributes.

The validation process is a standard procedure in machine learning and typically involves similar complexity, regardless of the specific type of model being evaluated. Typically, this involves splitting the available data into training and validation sets, where the model is trained on the training set and then evaluated on the validation set. Various metrics such as accuracy, precision, recall, and F1 score are available to evaluate the model's performance on the validation set in both workflows. However, it is more intuitive to interpret the result from the GLCM workflow. The last stage is producing a 3D visual model. CNNs and GLCM workflows can produce output in a probability volume, where high values indicate high confidence in the salt-body detection and low values indicate low confidence. It is necessary to convert the output from its ASCII format to the SEG-Y format, a common standard in the geoscience community for storing, exchanging, visualizing and ultimately, interpreting seismic data. As such, the development complexity, user experience, and model performance associated with the validation process and the visualization stage are generally similar for both GLCM and CNN-based workflows.

The feature-attributes framework is a powerful tool to help decompose complex ideas into manageable components. By breaking down an idea into its constituent features and attributes, we can evaluate and compare different aspects of the idea in a rigorous and structured manner from both novelty and usefulness perspectives.

Salt-body Detection via CNN	Novelty Matrix								Usefulness Matrix						
	Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model		Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model
Easy input data collection	2	0	0	2	2	0	0		4	0	0	4	4	0	0
Workflow ease of use	2	0	5	3	2	5	2		6	0	6	8	6	8	8
Model accuracy	0	0	7	3	0	7	0		0	0	6	6	0	5	0
Efficiency computations	2	4	7	4	2	6	2		8	6	4	4	8	4	8
Efficient HPC usage	2	2	6	3	2	4	2		8	5	2	4	8	2	8
Intuitive interpretations of predicted results	0	0	0	3	2	0	2		0	0	0	2	0	4	0
UI complexity	2	0	0	3	2	0	2		6	0	0	6	8	0	6
Integration with existing platforms	2	2	6	4	2	6	2		8	6	2	2	8	2	4
Project developing time	2	4	6	4	2	6	2		8	3	2	2	8	2	7
Maintenance and upgrade costs	2	3	6	4	2	6	2		7	3	2	3	8	5	6

Figure 4. Idea Matrix of Salt-body Detection via CNN.

2.3 Creativity Score

The creativity matrix is the Hadamard product of usefulness and novelty matrixes. Figure 5 shows the creativity matrix comparison between GLCM and CNN workflows. The GLCM workflow shows advantages in the intuitive interoperation of predicted results and product developing time attributes, while the CNN workflow leads to higher score in the model accuracy and UI complexity attributes. Adding the column entries and row entries of the matrix, the sums are listed at the bottom row and right column of the matrix, respectively. These sums indicate that the most important features are validation and prediction, which are directly related to the quality of end results. Workflow efficiency and development complexity are two key attributes.

We use the Frobenius norm as the creativity score for idea ranking. We get $\| C^{GLCM}{}_{10,7} \| = 119 < \| C^{CNN}{}_{10,7} \| = 128$; We can calculate the Frobenius norm on both novelty and usefulness matrixes. The results are:

$\| N^{GLCM}{}_{10,7} \| = 23 < \| N^{CNN}{}_{10,7} \| = 27$ and $\| U^{GLCM}{}_{10,7} \| = 42 > \| U^{CNN}{}_{10,7} \| = 41$.

Therefore, the detection of salt bodies benefits more from novelty in terms of creativity. Although both workflows are equally useful, the CNN workflow exhibits significantly greater novelty than GLCM workflow.

Salt-body Detection Creativity Matrix	GLCM Approach Creativity Matrix								CNN Approach Creativity Matrix							
	Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model	$\sum_{j=0}^{7} c_{ij}$	Acquisition of geological structure data	Training data for machine learning	Supervised machine learning	Validation using blind test data	Inference data preparation	Predict salt-body boundary on inference data	Producing a 3D visual model	$\sum_{j=0}^{7} c_{ij}$
Easy input data collection	8	0	0	8	8	0	0	24	8	0	0	8	8	0	0	24
Workflow ease of use	12	0	20	18	12	32	16	110	12	0	30	24	12	40	16	134
Model accuracy	0	0	25	12	0	20	0	57	0	0	42	18	0	35	0	95
Efficiency computations	16	20	25	15	16	15	16	126	16	24	28	16	16	24	16	140
Efficient HPC usage	16	8	16	15	16	12	16	102	16	10	12	12	16	8	16	90
Intuitive interpretations of predicted results	0	0	0	15	0	25	0	43	0	0	0	6	0	16	0	6
UI complexity	12	0	0	18	16	0	12	58	12	0	0	18	16	0	12	58
Integration with existing platforms	16	10	12	12	16	12	8	86	16	12	12	8	16	12	8	84
Project developing time	14	12	15	16	16	20	14	107	16	12	12	8	16	12	14	90
Maintenance and upgrade costs	14	9	15	16	16	30	12	112	14	9	12	12	16	30	12	105
$\sum_{i=0}^{10} c_{ij}$	108	59	128	145	116	166	94		110	67	148	130	116	161	94	

Figure 5. Creativity Matrix comparison between GLCM and CNN approaches.

3. Conclusion and Future Work

Innovation prevents energy companies from becoming stagnant and failing to adapt to changing market dynamics, customer preferences, and environmental pressures. To nurture innovation, a given process must commence with the generation of creative ideas, followed by the careful selection of the most promising ones. In this paper, we have applied a novel matrix-algebra framework for evaluating innovative ideas and facilitating informed decision-making to allocate resources optimally. This framework allows us to identify the most important components of the result and where improvements can be made in the process to mature an idea. By applying this evaluation framework to assess two real-world salt-body detection workflows, we have demonstrated the effectiveness of this approach in a repeatable and reproducible manner. Our findings suggest that this methodology can aid in identifying, pursuing, and operationalizing creative ideas to exploit their market potential fully.

The current method for generating the evaluation matrix involves conducting group discussions and gathering feedback from subject matter experts (SMEs). However, this approach heavily relies on the subjective opinions of the members. To enhance the scoring process, it is important to develop a more standardized evaluation that can be universally applied. Though much work remains, this study will encourage further research into developing and applying quantitative frameworks for innovative idea evaluation and decision-making in various fields.

References

[1] T.M. Amabile, *Creativity in Context: Update to the Social Psychology of Creativity*, Westview Press, Boulder, 1996.

[2] D.C. Brown, The curse of creativity, Gero, J.S. (Ed.), *Design Computing and Cognition*, DCC'10, 2010, pp. 157-170.

[3] J.C. Houtz and C. Patricola, Imagery, in Runco, A. and Prentky, S.R. (Eds), *Encyclopedia of Creativity*, Academic Press, San Diego, 1999, pp. 1-11.

[4] S. Hunter, T. Friedrich, K. Bedell and M. Mumford, Creative thought in real-world innovation, *Serbian Journal of Management*, 2006, V. 1(1), pp. 20-39.

[5] J.C. Kaufman and J. Baer, Hawking's Haiku, Madonna's math: why it is hard to be creative in every room of the house, in Sternberg, R.J., Grigorenko, E.L. and Singer, J.L. (Eds), *Creativity: From Potential to Realization*, American Psychological Association, Washington, 2004, pp. 3-12.

[6] Y.N. Kenett, M. Faust, A Semantic Network Cartography of the Creative Mind, *Trends in Cognitive Sciences*, 2019, Vol. 23(4), pp. 271-274.

[7] O.M. Khessina, J.A. Goncalo, V. Krause, It's time to sober up: The direct costs, side effects and long-term consequences of creativity and innovation, *Research in Organizational Behavior*, 2018, Vol. 38, pp. 107-135.

[8] A. Khurshid and S. Hardeo. Scales of measurements: an introduction and a selected bibliography. *Quality and Quantity*, 1993, Vol. 27, pp. 303-324.

[9] R.S. Nickerson, Enhancing creativity, in Sternberg, R.J. (Ed.), *Handbook of Creativity*, Cambridge University Press, Cambridge, 1999, pp. 392-430.

[10] S. Nilsson, J. Wallin, A. Benaim, M.C. Annosi, R. Berntsson, S. Ritzén and, & M. Magnusson, Re-thinking Innovation Measurement to Manage Innovation-Related Dichotomies in Practice. *The 13th International CINet Conference - Continuous Innovation Network Conference*. 2012.

[11] V. Tang, Matrix representation of ideas: stimulating creativity using matrix Algebra, *International Journal of Innovation Science*, 2018, Vol. 11(4), pp. 489-538.

[12] T.L. Saaty, Hierarchies, reciprocal matrices, and ratio scales, in W.F. Lucas et al. (eds.) *Discrete and System Models*, Springer, New York, 1983, pp. 218-253.

[13] T.L. Saaty, *Decision Making: The Analytic Hierarch Process*, University of Pittsburgh, Pittsburgh, 1988.

[14] P. Sarkar and A. Chakrabarti, Assessing design creativity, *Design Studies*, 2011, Vol. 32, No. 4, pp. 348-383.

[15] S.K. Sim and A.H. Duffy, Knowledge transformers: a link between learning and creativity, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 2004, Vol. 18, No. 3, pp. 271-279.

[16] D.K. Simonton, Creativity as a constrained stochastic process, in Sternberg, R.J., Grigorenko, E.L. and Singer, J.L. (Eds), *Creativity: From Potential to Realization*, American Psychological Association, Washington, 2004, pp. 83-101.

[17] B.M. Staw An evolutionary approach to creativity and innovation. In M. A. West, & J. L. Farr (Eds.), *Innovation and creativity at work: Psychological and organizational strategies*, 1990, pp. 287–308. John Wiley & Sons, Oxford.

[18] R.J. Sternberg, J.C. Kaufman and J.E. Pretz, *The Creativity Conundrum*, Psychology Press, New York, 2002.

[19] R.J. Sternberg and T.I. Lubart, The concept of creativity: Prospects and paradigms. In R. J. Sternberg (Ed.) *Handbook of creativity*, Cambridge University Press, Cambridge, 1999, pp. 3-15.

[20] G. Strang, *Linear Algebra and Its Applications*, 3rd ed., Harcourt Brace Jovanovich, Publishers, San Diego, 1976.

[21] R.W. Weisberg, *Creativity: Understanding Innovation in Problem Solving, Science, Invention, and the Arts*, John Wiley, Hoboken, 2006.