Industrial revolution 4.0, renewable energy: A content analysis

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Abstract: The aim of this paper is to demonstrate the applicability and value of qualitative research methods (i.e. Content analysis) in the scientific fields. The sample was collected in light of the fourth industrial revolution and renewable energy papers publish in the first half of 2018. a combination of qualitative and quantitative methods were applied. Our results shed light on potential applications of such analytical techniques in natural science. In our specific sample, we were able to identify the major drivers of research in the field of renewable energy given the advances of fourth industrial revolution.

Keywords: Qualitative Content Analysis, Fourth Industrial Revolution, Renewable Energy, C-Coefficient, Pearson's correlation

1 Introduction

Mayring (2000) defined Qualitative Content Analysis (QCA) as a family of systematic, rule-guided techniques used to analyze the informational contents of textual data. Different methods have been developed within the context of content analysis, which includes both qualitative and quantitative methods, with both sharing the central feature of systematically categorizing textual input data to generate sense out of the qualitative as well as the quantitative generated components of the data under analysis (Forman and Damschroder 2007).

Content analysis is currently an established method that also may be used to gain insight into natural sciences fields. In the field of sustainability, major economies around the globe are currently emphasizing technological development on renewable energy sustainability over the currently used finite conventional fossil fuels. This prospect has recently started expansion to third world countries such as Jordan (Al Shafeey and Harb 2018), where energy resources are scarce, with the push of energy cost mitigation as the main adoption driver together with the global contribution to reducing environmental impact of fossil fuels (Gross, Leach et al. 2003, Boyle 2004). Further, Content analysis has been used previously to advance the understanding of agricultural sustainability by (Velten et al., 2015).

Industry in general plays a major role in economic development and growth as with every industrial leap, material goods get mechanized and automated to a further dimension of applicability. The "Industrial Revolution" as a term is utilized to refer to specific high impact technological developments which lead to paradigm shifts in all aspects of human civilization. The first industrial revolution was triggered by the technological discoveries in the field of mechanization, followed by the intensive use of electrical energy, which is referred to as the second industrial revolution. The third and fourth industrial revolutions are both linked to Digitalization but on two very different levels (Lasi, Fettke et al. 2014).

The third industrial revolution is related to increased accessibility and widespread of digitalization, while the fourth industrial revolution is rather related to the combination of internet technologies and smart objects, where machines and products can interact with each other through sensors coupled with Artificial Indigence (AI) algorithms, to produce more targeted products through an autonomous control system. The resulting interaction is the newest paradigm shift to date and its currently on the rise. Furthermore, Given the sub advances that are expected in the current industrial revolution; the term "Industry 4.0" was established to mimic software versioning nomenclature (Lasi, Fettke et al. 2014).The term was first used in 2011, and is defined as the collective technologies of a value chain creating a unified cyber-physical system (CPS); Internet of Things, Internet of Services (IoT, IoS); Internet of People (IoP); and Internet of Energy (IoE) (Lom, Pribyl et al. 2016).

Currently, both fields of industrial revolution and renewable energy are considered hot topics. In this work we will be exploring the potential and applicability of qualitative research methods (i.e. QCA) in the scientific fields. As an example, we will be using renewable energy as our main theme and we will be investigating the relationship between renewable energy and the fourth Industrial revolution using a combination of qualitative and quantitative methods. Our results will shed some light on the potential uses of such analytical techniques in natural science. Different statistical software analysis tools in conjunction with textual analysis tools were utilized to identify the level of correlation between extracted codes finally leading to generating a level array. In the following sections, the methodological approaches adopted will be detailed, results summarized and further discussed and ultimately concluded.

2 Methodology

Content analysis in natural sciences is the major theme of our work. As an example, we will be investigating the relationship of "industrial revolutions 4.0" published articles, which referred to "renewable energy" in their context. The methodology utilized for this work is a combination method of qualitative and quantitative analysis.

To gather data for the work, the researchers obtained and analyzed the studies published during the first half of 2018. ScienceDirect was chosen as a database for our search, given its multidisciplinary publishing nature. The term "Industrial Revolution 4.0" was set to be the main search term. In addition, "renewable energy" term was conjunctly used to look in the "title, abstract or keywords field". The search engine was set to look only for "research papers". Fourteen papers in total were obtained, of which four papers were agreed upon by the authors for exclusion. Ten articles were finally selected and analyzed. These papers are summarized in Table 1. Exclusion of papers was based on either irrelevance or out of date range. For instance, articles published before January, 2017 and after June, 2018 were excluded. also, articles irrelevant to our specified field of study were further eliminated. After careful assessment of the papers by all the researchers, articles which did not meet our selection criteria were excluded.

For the analysis part, qualitative tools were used to obtain word frequencies and generate our codes deductively. Codes were generated by "Atlas.Ti" software, Later; the resulting data from Atlas.Ti was migrated to SPSS in order to perform the statistical quantitative tests required for our work such as occurrence, co-coefficient relation, and Pearson's correlation.

3 Results

Table 1 shows the articles selected after applying the search criteria for the analysis. The papers were retrieved, converted into text documents and then imported to ATLAS.ti software. the coding process started with condensation of the transcribed text to finally generate 17 codes. Table 2 shows our generated codes and their frequency. C-Coefficient was then used to indicate the strength of the relation between each two codes and the generated values were then exported to SPSS software to conduct further statistical analysis. In SPSS, Pearson's correlation was used to identify the relationship linearity between each two codes.

Table 1. Selected research papers and their corresponding authors.

No.	Title	Author/s
1	A Pathway Towards Sustainable Manufacturing for Mid-size Manufacturers	Jun-Ki Choi, Ryan Schuessler, Michael Ising, Daniel Kelley, Kelly Kissock
2	Agent-Based Simulation Model of Virtual Power Plants for greener Manufacturing	Stefan Woltmann, Maximilian Zarte, Julia Kittel, Agnes Pechmann
3	An IoT based approach for energy flexible control of production systems	Julia Schulz, Richard S.-H. Popp, Valerie M. Scharmer, Michael F. Zaeh
4	China's energy revolution strategy into 2030	Qilin Liu, Qi Lei, Huiming Xu, Jiahai Yuan
5	Comparative analysis for solar energy based learning factory: Case Study for TU Braunschweig and BITS Pilani, Procedia CIRP	Kuldip Singh Sangwan, Christoph Herrmann, Manoj S. Soni, Sanjeev Jakhar, Gerrit Posselt, Nitesh Sihag, Vikrant Bhakar
6	Energy modeling approach to the global energy-mineral nexus: Exploring metal requirements and the well-below 2 °C target with 100 percent renewable energy	Koji Tokimatsu, Mikael Hook, Benjamin McLellan, Henrik Wachtmeister, Shinsuke Murakami, Rieko Yasuoka, Masahiro Nishio
7	Financing renewable energy: Who is financing what and why it matters	Mariana Mazzucato, Gregor Semieniuk
8	Population growth, urbanization, and electricity - Challenges and initiatives in the state of Punjab, India	Ritu Raj Kaur, Ashwani Luthra
9	The achievement of the carbon emissions peak in China: The role of energy consumption structure optimization	Shiwei Yu, Shuhong Zheng, Xia Li
10	The role that battery and water storage play in Saudi Arabia's transition to an integrated 100% renewable energy power system	Upeksha Caldera, Christian Breyer

Table 2. ATLAS.ti generated codes and their corresponding frequencies

Climate	Coal	Development	Electricity	Emissions	Energy	Energy Demand	Finance	Gas	Industry	IoT	Manufacturing	Peak	Photovoltaics	policies	storage systems	sustainability	Total
49	77	122	198	185	792	4	134	119	43	22	82	119	145	38	134	44	2307

3.1 C-Coefficient

The C-Coefficient was used to indicate the strength of the relationship between codes (Smit, 2012). C-Coefficient can take any value between zero and one; zero means codes do not co-occur, and one indicates that these two codes co-occur wherever they are used. The closer the C-Coefficient to one, the stronger relation is. (Lewis, 2016) The C-Coefficient was calculated using the equation (1) which was simulated through ATLAS.ti. Where $n12$ is the co-occurrence frequency between the two codes $c1$ and$c2$, whereby $n1$ and $n2$ are their occurrence frequency. Results are shown in Table 3.

$$C = \frac{n12}{n1 + n2} - n12 \qquad (1)$$

The results show that the highest C-Coefficient was between "emissions" and "peak" codes with a value of 0.8. That indicates that "emissions" were discussed as "peak emissions" most of the time. The result indicates the direction of the studied population was to study the "peak emissions" as an important part of studying emissions.

Other high C-Coefficient values were seen between the codes "sustainability" and "development", "energy" and "emissions", "electricity" and "development", "manufacturing" and "development". Table 3 shows C-Coefficient results for the mentioned codes. The results of the C-Coefficient analysis show that some aspects of fourth industrial revolution like sustainability and development (Stock and Seliger, 2016) were related. While other aspects were not significantly related.

Table 3. C-Coefficient values between the selected codes generated by ATLAS.ti

	Energy	Electricity	emissions	Development	peak	Manufacturing	sustainability
Energy		144 - 0.17	246 - 0.34	119 - 0.15	38 - 0.04	126 - 0.17	48 - 0.06
Electricity	144 - 0.17		49 - 0.15	60 - 0.23	19 - 0.06	12 - 0.04	6 - 0.03
emissions	246 - 0.34	49 - 0.15		23 - 0.08	135 - 0.80	32 - 0.14	17 - 0.08
Development	119 - 0.15	60 - 0.23	23 - 0.08		7 - 0.03	53 - 0.35	39 - 0.31
peak	38 - 0.04	19 - 0.06	135 - 0.80	7 - 0.03		3 - 0.02	1 - 0.01
Manufacturing	126 - 0.17	12 - 0.04	32 - 0.14	53 - 0.35	3 - 0.02		90 - 2.50
sustainability	48 - 0.06	6 - 0.03	17 - 0.08	39 - 0.31	1 - 0.01	90 - 2.50	

The C-Coefficient table shows the relation between two codes; however, it doesn't show the strength of a linear relationship between paired data (a whole column and a raw). furthermore, the C-Coefficient tables doesn't provide enough information about the relation between "industrial revolution 4.0" and "renewable energy". Each code in this research have seventeen C-Coefficient values indicating the relation between each code and the other sixteen codes. Thereby, a further investigation can be done and the linear relationships between two sets of data can be analysed. Accordingly, Pearson's correlation coefficient was used to find the relations between these sets of codes (Sedgwick, 2012).

3.2 Pearson's Correlation

Pearson's correlation coefficient is a statistical measure of the strength of a linear relationship between paired data, it is symbolized by r and is by design constrained in value between 1 and -1. the closer the value is to 1 or –1, the stronger the linear correlation.

$$-1 \geq r \geq 1 \tag{2}$$

To put Pearson's correlation into categories, (Evans, 1996) suggested a categorization system for the absolute value of r: 0.00-.19 "very weak", 0.20-.39 "weak", 0.40-.59 "moderate", 0.60-.79 "strong", .80-1.0 "very strong".

Pearson's correlation was applied to the previously obtained C-Coefficient values from ATLAS.ti. It was calculated for each set of codes in order to identify the correlation direction and strength of the relations between sets of codes. The results show that most of the r values were positive, some sets show very strong linear relations, other sets varied between "strong" to "very weak". Here in this study, the "very strong" linear relation was a main focus. The Pearson's correlation analysis shows that the "energy" and "peak" sets of data and "industry" and "sustainability" sets of data both has a very strong linear correlation as can be seen from Pearson's results in table 4.

It was observed that "energy" and "peak" shows a very strong linear relation, while table 3 above shows an insignificant C-Coefficient between the two codes. Pearson's correlation shows the strength of a linear relationship between paired data. Here the .803 r value shows a very strong linear relation between "energy" and "peak", which means whenever authors in this research's population were discussing "peak" regarding the other sixteen codes, "energy" was discussed as well regarding to the other sixteen codes. In other words, the more "energy" was discussed is the more "peak" was discussed too.

Table 4. Pearson's Correlation results

Code	Energy	Peak	Code	Industry	sustainability
Energy	1	.803**	Industry	1	.896**
peak	.803**	1	sustainability	.896**	1

**Results are significant. Correlation is significant at the 0.01 level (2-tailed).

The results show that even though "energy" and "peak" was not discussed together many times, yet they are highly related. "energy" and "peak" have strong linear relation, and the more “energy” was discussed the more “peak” pondered. The same conclusion can be made for the relation between “industry” and “sustainability”. Whenever the authors discussed “industry”, “sustainability” also was concomitantly discussed with regard to the other sixteen codes. Hence industrial sustainability was one of the major research themes to an extent.

It was found by the Pearson’s correlation test that not all the aspects of industrial revolution 4.0 were related to renewable energy. Other aspects of industrial revolution 4.0 such as; Decentralization, Real-Time Capability and Modularity were not mentioned in the selected publications (Lom, Pribyl et al. 2016).

Conclusions

This study was aimed to demonstrate the applicability of content analysis in natural sciences. From our selected paper population, it can be concluded that content analysis can be used for data extraction and analysis. In this study content analysis was used for finding the relations between different aspects of industrial revolution 4.0 and renewable energy. Our results demonstrate how certain fields relate and inter-connect with each other. Further, using our mixed methodology, we were able to quantify the level of correlation between the studied terms. This work can shed light on the degree of inter-connectedness between two specific topics.

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