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Leveraging e-Commerce Performance through Machine Learning Algorithms

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A R T I C L E I N F O

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A B S T R A C T

Machine learning (ML) is quickly emerging as a new discipline and resembles to be an attractive alternative to statistical methods in various industries. An appreciation of the possible applications of ML in digital marketing and eCommerce will be proposed in this article. The authors will examine qualitative determinant factors on brand logos and correlations on companies income, with profit, the number of employees, images and number of product images on eCommerce homepage. 1420 Romanian companies were analyzed in this research in order to identify specific factors that determines the success of an eCommerce business.

1. Introduction

Throughout time marketing research branched out and taken various forms. Different methodologies, classifications, techniques and systems were developed to serve relevant and timely information to competitive managers (Kotler, 2002). No matter the taxonomy used, as long as it provided reliable, consistent, accurate data, and actionable market intelligence, scholars appreciated and documented it. In today's digital commerce, out of the box solutions enable businesses to deploy eCommerce websites with analytics systems quickly or easily integrated with third parties. Still, when it comes to determining the identity of the brand or product, business owners face uncertainty. Considered a creative process, it is a matter of understanding the business owner or the marketing executive preferences, and how these two actors understand the targeted audience. The satisfaction level on these services is always dependent on the industry maturity and how the perceived value influences the end customers throughout the purchasing process (C. A. Adams & Frost, 2004).

This article examines how previous authors took into attention the technical factors of eCommerce websites and available solutions for digital marketing. Based on the Nielsen model (1999), we will identify key factors in design quality impacting the overall success of a business, in order to better understand the deciding determinants in consumer behaviour and key performance indicators in eCommerce. In chapter 3 will attempt to classify brand logos, banners and screenshots of the eCommerce website based on factors like the company's founding year, number of employees and turnover. In order to achieve this, a custom model to classify images will be trained on the Google Cloud platform with AutoML Vision toolkit. The ML algorithm is trained on 1420 Romanian eCommerce websites that, by law, have to place on the homepage or terms of condition page the company name and the VAT number. With that, a Pearson correlation test is performed based on the financial information of the companies.

As Hoffman & Novak attempted in 1996 to establish a "new medium-as-market" on the world wide web, the objective of this article is to identify new qualitative factors that might serve as deciding factors for online consumers, as the digital ad spending surpasses traditional marketing spending in the US (K. Bryan, 2019).

2. Literature review

Currently, businesses use eCommerce applications on both desktop computers and smartphones as digital marketing instruments, and these solutions have brought much awareness from both users and academicians regarding technological novelty. Information technologies (ITs) have radically transformed the way people buy, get information and use everyday products. Therefore, digital marketing and eCommerce are the main channels that businesses use to introduce new or existing products. Zhuofan et al. propose a

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conceptual framework in order to optimise the resource allocation and production process of an eCommerce platforms and parts website quality as follows: (1) brand awareness, (2) visitors scale, (3) user experience, (4) website speed, (5) interactive.

This research will be centred mostly on brand awareness and user experience, considering the sample we are analysing. Furthermore, we will examine the following graphical elements contained in an eCommerce website:

- brand logo
- banners and sliders
- promotional banners
- payment option/shipping methods banners
- product discount carousels
- product images

2.1 Logos

A company's logo acts as a critical asset in solving the challenge of indistinguishability and often decreases communication efforts for the marketing staff (Bettels & Wiedmann, 2019). Following the point of view of Jiang, Gorn & Galli, consumers can create mental imagery based on the logo, and reconstruct that image of the product without actually seeing the product. Thus the perceived value of the product or service is associated with the mental imagery of the brand logo. Based on this assumption, well-known brands started redesigning campaigns to simplify the brand logo(ex. Pepsi, Starbucks, Apple). This simplification follows the flat design trend that is defined by a straightforward and iconic nature (Bossel, Geyskens & Goukens). Of course, this simplification will create more challenges to identify uniqueness and maintain brand originality in a more and more competitive market. In this sense, Kumar et al. proposed a computer vision model that classifies logos based on the text, colour or symbol for ease of identification of counterfeits. Not considering this factor can have implications beyond economic nature. Park el Al. suggested a conceptual framework based on several factors identified in the firm's logo and how it influences a company's market performance. Out of this resulted managerial, strategic insights to acknowledge logos as more efficient agents in the relationship with consumers, considering it provides aesthetic gratification. Identifying supported confirmation that there is a correlation between the value assessment of a business and the design of the brand logo is an ambitious endeavour. However, trying to classify the logos using machine learning might show that there is a qualitative difference between the turnover and how the current design of the firm's identity. Other dimensions are important as well as customer’s brand commitment, functional benefit in communication, patent citations, visual gratification, revenue growth and brand familiarity as Park et Al. points out. Even so, analysing the impact of the logo in a crowdfunding campaign might be the most conclusive analysis, considering that the start-up has no previous trackable history. In this matter, Mahmooda et al. conducted research using heuristic methods into identifying if visual cues in the brand logo have an impact on backers impact in supporting a particular project.

2.2 Ecommerce usability and user experience

Given the substantial investment in eCommerce platforms, firms need more reliable methods concerning the examination on the usability of their software solutions before launching. Web usability studies regularly relied on questionnaire distribution as a unique approach to evaluate users' opinions of the website. Unfortunately, this method can be applied after the eCommerce solution/website is launched. There is enough proof to suggest that if users find it challenging to process product information or go through check out process, their opinion of the brand alters. Websites with inadequate design indicate an inferior brand reputation (Song & Schwarz, 2008).

As pointed by Alonso-Virgós et al. website usability and overall graphics concerning user experience are directly affected by the web developer prior experience and training. Furthermore, it is crucial to follow the most current guidelines and implement them adequately.

Hornbæk (2006) asserted in his review that usability is not directly measured, considering the polymorphic state of qualitative work. For this reason, one must use existing models and indicators to quantify the usability of a website or a particular webpage. Out of the several proposed methods in the literature review, Fernandez et al. (2011) distinguish two main categories: empirical methods and inspection methods. If the former might appear rather usual for the latter one, the researcher has to take into consideration a range of factors like the bounce rate, average visit duration, the number of pages visited per session and conversion rate.

Nielsen (1999) proposes five quality attributes to assess the usability of user interfaces quickly and defines the terms as "methods to improve the ease-of-use during the design process."

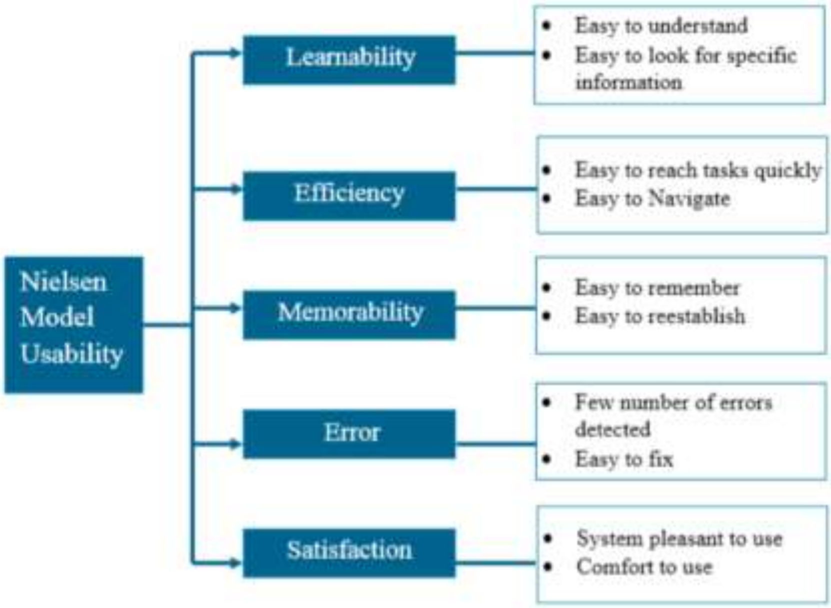


Fig. 1. Nielsen model using five usability attributes (J. Nielsen, 1999)

2.3 Banner Ads on eCommerce websites

A banner ad is a graphical element of advertisement displayed on an eCommerce website. Considered the most frequently used types of web advertisements by Cho, Lee, & Tharp (2001), banners are used to present discounted offers and value-added client benefits. Usually, they contain a call to action text with a hyperlink to a specific product or landing page for more details information (Li & Bukovac, 1999).

Even if 80% of users do not notice them (Banner Blindness) (Benway, 1998), it remains the optimal communication method to attract viewers' attention to specific products, offers or discounts. Banner blindness can happen to internet users that acquired a specific type of experience in surfing automatically, ignoring advertisements and other distractions which look similar to ad banners (Benway & Lane, 1998). Even so, the user attention considerably drops to this type of content when he identifies specific patterns that allow him to filter the content easily, no matter if it is text, images or videos (Hsieh et al. 2012). Even if the animation slightly increases the eye fixation on the banners, the real benefit is in user recalling better this piece of content. In accordance with the point of view of Hamborg et al. (2012), animated banners tend to be more effective than non-animated ones, and the study was validated using eye-tracking technology and a set of questionnaires.

When exaggerated, or aggressive banners tend to have the opposite effect, somehow ruining the reputation or the brand or of the firm. Internet users consider pop-ups irritating and frustrating because they are interrupting the flow of actions they were pursuing. These negative emotions usually interrupt the intention of buying and tends to be associated with the identity of the brand (G. S. Bahr, R. A. Ford, 2011). Instead, polite interactions and fluid communication in banner ads can increase the rate of conversion on an eCommerce website. Even if banners started mostly on desktop computers, the market of smartphones and online media-services (TV streaming) increased as well.

2.4 Machine learning in marketing

We have studied popular search engines for academic articles as google scholar, science direct and research gate searching various keywords in order to identify articles in marketing journals on the machine learning topic. Even if the first articles in marketing journals included machine learning since 1998 (C. X. Ling and Chenghui Li) only in 2019, it gained momentum with more than 21 articles. The sudden rise is determined by the number of tools available for the general public and the ease of doing experiments. The first article found listed just the methodology as a potential breakthrough and how this can impact the marketing research and marketing intelligence division of companies. On the other hand, in 2019, we can see applied experiments on specific marketing issues, proposing applications and advanced decision-making system for complex business (G. Stalidis, D. Karapistolis and A Vafeiadis, 2019). The full list of articles can be seen in appendix 1.

1998	2
2001	1
2002	2
2003	1
2005	2
2006	1
2013	3
2014	2
2015	1
2017	1
2018	3
2019	21
2020	1

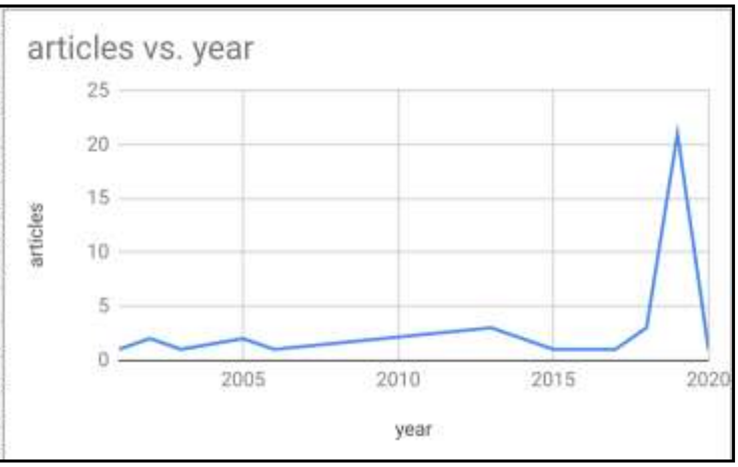


Fig. 2. Machine learning articles evolution over time

Exploiting the enormous volume of data available in the current eCommerce application and social media systems generated by, the web is becoming more accessible in order to deliver marketing intelligence. Significant efforts have been made in the development of decision assistance systems for an eCommerce platform, based on information gathered by analytics software(G. Stalidis, D. Karapistolis and A Vafeiadis, 2019). Data analytics, big data, predictive modelling and data mining, are quickly integrated with turnkey solutions, becoming powerful tools in modern marketing. Most of these solutions make use of Neural Networks as the primary tool, considering the concept is emulating the function of the human brain.

Xia Liu proposes a five-step process on how these solutions should be integrated into the user-generated content analysis of B2B company performance:

1. Data Collection - Identification of Data Source
2. Text Preprocessing - Structured Text Data, Tokenization
3. Data Visualization - Word Cloud and LDA
4. Data Integration/Aggregation - Structured Text Data and Panel Data
5. Data Analysis - Data Analysis Results

In both data aggregation and data analysis, using machine learning methods can be used to process and transform "unstructured big data" into "small structured data" (Xia Liu, 2019).

3. Romanian eCommerce companies Analysis

For this analysis, it has been used a sample of 1420 companies activating in the digital commerce area. Furthermore, considering the data was collected from Romanian companies that under the law 26/1990 are required to publicly list information about the turnover number of employees, the year the company was founded and other financial information. Another critical factor in making this research possible was that under the law 441/2006, article 74, all companies that are promoting products online should have the VAT number available on the homepage and contact page. Based on this information, a database of 2372 companies was created with financial information and corresponding eCommerce website URL, from where elements of identity were collected. The difference of 952 companies out of various reasons (robots.txt, website not available or the logo could not be easily identified) was not included in this study.

Using python Jupyter lab, the logos samples were prepared for Image Classification tool in google cloud vision, in order to train a model that will be able to classify brand logo in two categories with companies established before and after 2010. For an accurate prediction, each labelled sample should have at least 100 images. All images should be categorised with a specific label (year, number of employees). Because the number of images was before 500 Google Cloud Storage was used to upload the images and all images have to be in one of the following formats: JPG, PNG, GIF, BMP, ICO.

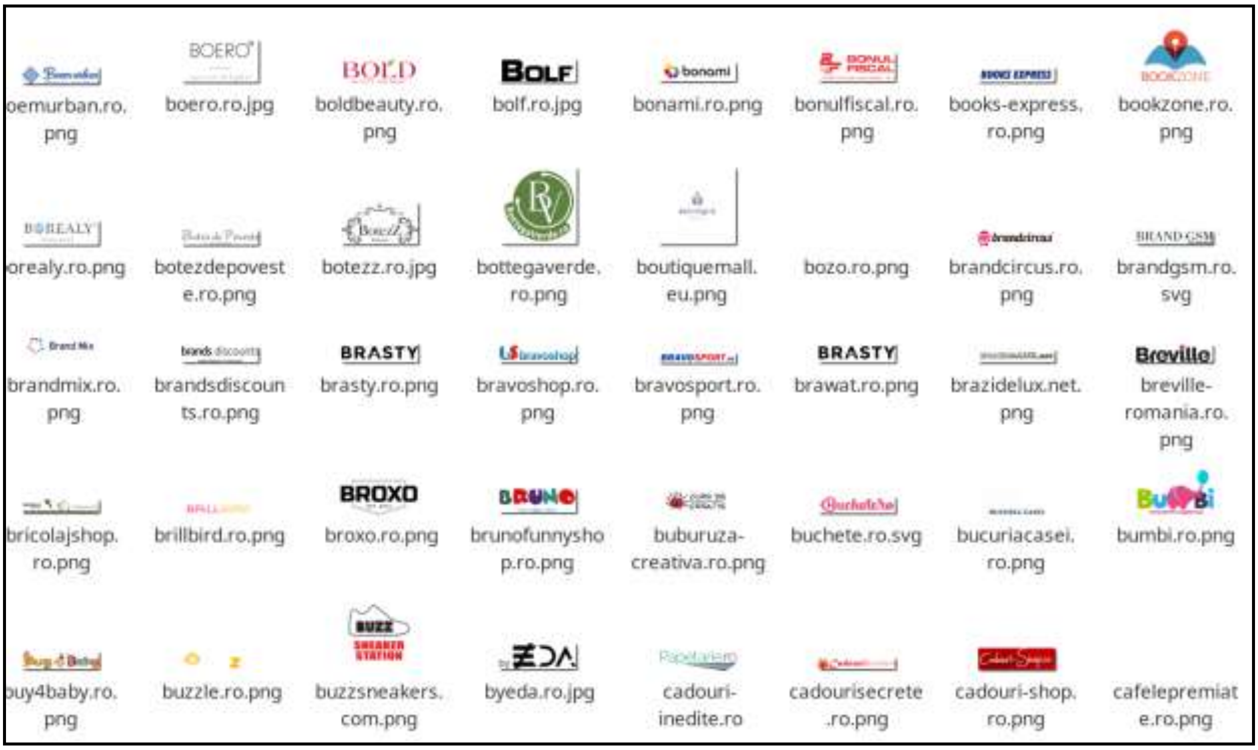


Fig. 3. Sample of the analysed logos

Also, the number of images on the homepage was mined for each eCommerce website and labelled as logo, banners or product images using a set of regular expressions as follows:

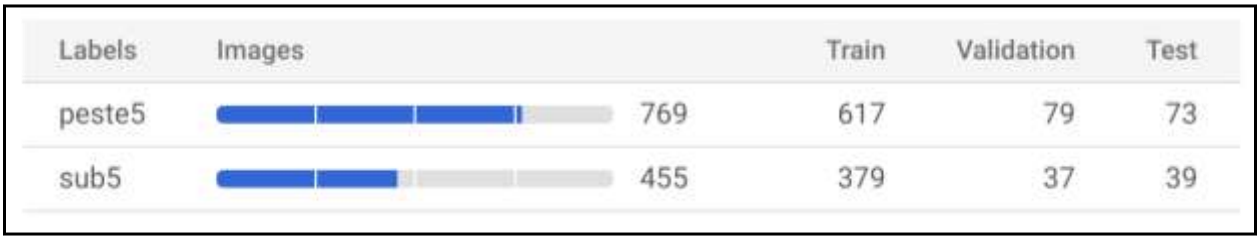
- Brand logo - logo|identity|brand|identitate
- Banners - banner|baner|promo|slider|carousel|slideshow|slide
- Products - product|produse|item

The objective of the study was to identify the strength of the association based on the Pearson correlation coefficient, taking into consideration the financial variables and number of images identified on the website's homepage. Pearson's correlation is utilised to identify a linear relationship and to test whether two variables have a positive or negative relationship, interpreting the results between the value of +1 to -1. Naturally, the financial information of the companies indicated a very strong positive correlation; the obtained *r value* for income and spending was 0.99. Also, a very strong correlation was encountered between the merchandise stocks and the number of employees (r=0.84). Interestingly, the profits in 2018 are negatively weak correlated with the liability of the companies and very weak with the number of employees. Even if there is a moderate correlation between the number of images on the homepage and the product images, these indicators are very weakly correlated with the financial indicators. The matrix of Pearson r values is listed below.

	Angajati2018	Datorii2018EUR	Stocuri2018EUR	Profit2018EUR	Cheltuieli2018EUR	Cifra2018EUR	NumarImagini	NumarBanere	NumarProduse
Angajati2018	1	0.842543	0.84677	0.150907	0.839347	0.845398	0.00118969	0.0472287	-0.0143328
Datorii2018EUR	0.842543	1	0.97724	-0.201747	0.984277	0.98208	0.00155902	0.0638681	-0.00215178
Stocuri2018EUR	0.84677	0.97724	1	-0.128135	0.97194	0.971459	-0.00514803	0.0521633	-0.0111864
Profit2018EUR	0.150907	-0.201747	-0.128135	1	-0.144188	-0.118452	-0.00314518	-0.0272778	-0.00717647
Cheltuieli2018EUR	0.839347	0.984277	0.97194	-0.144188	1	0.999604	-0.00512925	0.0503687	-0.00752419
Cifra2018EUR	0.845398	0.98208	0.971459	-0.118452	0.999604	1	-0.00498454	0.0496795	-0.00753032
NumarImagini	0.00118969	0.00155902	-0.00514803	-0.00314518	-0.00512925	-0.00498454	1	0.305966	0.564875
NumarBanere	0.0472287	0.0638681	0.0521633	-0.0272778	0.0503687	0.0496795	0.305966	1	0.150799
NumarProduse	-0.0143328	-0.00215178	-0.0111864	-0.00717647	-0.00752419	-0.00753032	0.564875	0.150799	1

Fig. 4. Pearson R correlation matrix, the output of python pandas

For this classification, two different datasets were created, one for the year of establishment and one for the number of employees, with 1,224 and respectively 1223 labelled images.
Each of the datasets was grouped in different subsets in order to train, validate and test the custom model that built in this process, see figure 5.



Labels	Images		Train	Validation	Test
peste5		769	617	79	73
sub5		455	379	37	39

Fig. 5. Subsets of images for the training of the model. Screenshot Google cloud vision

The trained model attempts multiple parameters while searching for recognizable patterns in the uploaded training dataset. As this machine learning model identifies recognizable patterns, it uses the validation dataset to test it. The algorithms that are having the best performance are selected from the ones distinguished throughout the training step.

The last step in the Google AutoML Vision Image Classification, after the patterns have been identified, is to test for accuracy, error rate and quality and using the validation and test subset.

The training for the two datasets took more than a day (28 compute hours). The price for a compute hour is $20, and the trained model can be used as an API or exported for edge processing in TensorFlow.

The results of the training process, is available in the Confusion Matrix and listed in the figure below, can give us specific information on how the trained model performed for each subset that was configured.

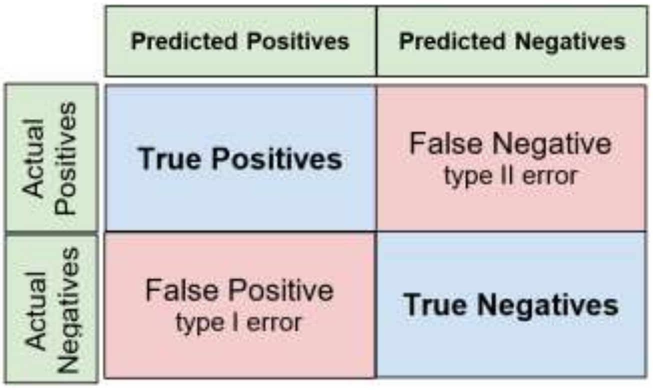


Fig. 6. Explanation of the confusion matrix based on Stehman's error matrix (1997)

To visualise the results, there are a couple of other visuals based on the Confidence threshold score that refers to the level of confidence the trained model has assigned to a category for a tested item. Depending on the level of confidence score that can be set manually on a scale from 0 to 1, there are two other indicators that we need to take into consideration:

- Precision - shows a ratio of all the assigned tests examples that were a label to how many were supposed to be classified. In a very high precision trained model, there are fewer false positives.
- Recall - the fraction of the examples that should have had the label that is successfully retrieved out of the total assigned labels. A high recall trained model generates less false negatives.

$$\text{Precision} = \frac{tp}{tp + fp} \qquad \text{Recall} = \frac{tp}{tp + fn}$$

For the analysis based on the number of employees, the trained model was tested on 112 images, three levels of confidence threshold were examined in order to predict companies with more than five employees based on the brand logo:

Table 1. Confidence threshold table

Confidence threshold	Precision ratio	True Positives (Correctly identified)	False Positives
0.5	68.32%	59	32
0.65	71.43%	37	18

Confidence threshold	Precision ratio	True Positives (Correctly identified)	False Positives
0.73	72.97%	25	12
0.5	55.17%	44	39
0.65	60.27%	40	29
0.73	66%	33	21

As can be seen, the trained model for the number of employees performed better than the year of establishment of companies on the tested sample. Depending on the rigorously of the analysis, different levels of confidence threshold can be selected, but also an indispensable factor needed to be taken into consideration as well: the recall value that shows us the ratio including false negatives; the correct labelling of logos for firms with less than five employees. For this analysis, the recall value was 24%, and AutoML Vision recommends higher values for better results. For a similar experiment on x-ray scans on patient's chest, in order to identify pneumonia, the recall value obtained was 87.5%, the sample used in this experiment was 5.824 images (Reifschneider, 2019). Considering the sample for brand logo analysis was 1.224, a more significant sample might improve the results for this test.

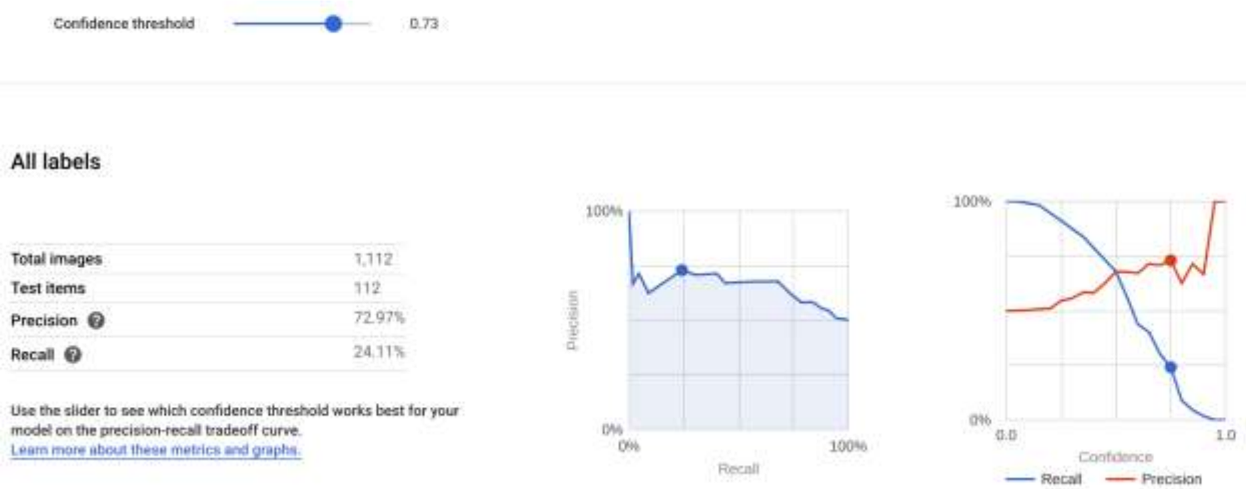


Fig. 7. Google vision trained algorithm based on number of employees output

4. Conclusion and Managerial Implications

Putting this together with the Miesen's usability model, we can confidently claim that we can develop Machine learning models to deal with the satisfaction and memorability dimensions. Even so, the current research only looks at particular elements in trying to assess the qualitative properties of a logo. Further models can be trained in order to check a plethora of characteristics based on quantitative metrics or qualitative data gathered from online platforms like Mechanical Turk. Based on these models, managers can better assess the quality of creative employees and test particular graphical elements before running them online. Moreover, Artificial Intelligent modules can be integrated with traffic analytics systems in order to test specific landing pages on trained models of customer behaviours on other e-commerce pages. Moreover, combining statistical tests like the Pearson r test can bring considerable benefits to an eCommerce solution. Revealing consumer behaviour correlation, a dashboard with key performance indicators in real-time can be an excellent source of information for managerial decision making in a dynamic digital market. The information gathered from consumers should always be correlated with external sources like competitors financial data for better insights and an extensive overview of the market. Current eCommerce solutions come by default with tools to analyse visitors traffic and behaviour, but usually, they need integration with third-party solutions using web 2.0 standards to gain more marketing insights. To honestly approach the digital transformation challenge, one must consider better ways to understand the data generated from consumers and competition with the tools available online for the benefit of marketing intelligence.

The implementation of machine learning solutions in managing tertiary sector activities (services) it produces unprecedented implications on how organisations can lead and build new products. Qualitative evaluation of services is time-consuming and can lead to legal issues if there is a lack of specific KPI's. By using machine learning to align client's expectations better and to create quantifiable indicators on how the service should be delivered, it is imperative to a sustainable economy. Translating the customer's preference into instructions that a trained algorithm can evaluate promptly will increase customer satisfaction.

5. Limitation and Future research

Even though for a statistical test, the sample was acceptable for training a machine learning algorithm, it was moderately small. With a more significant sample, a more precise model can be developed and be trained to take into consideration different labels in evaluating the actual qualitative state of an actual logo. A comparative analysis of samples from different countries, industries or fortune 500 company can show characteristics in design patterns. Furthermore, the analysis can be extended to other types of graphical materials like promotional banners, flyers and screenshot of the entire website. Dividing the banners into subcategories like promotions, payment options, shipping details, type of support offered and home page slider can bring significant insights on how to better optimise digital marketing campaigns.

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