Artificial Intelligence in Marketing Analytics: The Application of Artificial Neural Networks for Brand Image Measurement

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Addressing the high complexity of brand image measurement, the present research paper investigates the use of artificial neural networks in this particular application context. Since profound insights into the image of a brand are essential for management, the deployment of this learning algorithm is considered as it allows modeling of complex non-linear and multilayered relationships. The conceptual approach presented in the paper is illustrated with the empirical example of the sportswear manufacturer adidas. By using quantitative survey data, a multilayer artificial neural network is created to link the evaluations of specific brand attributes with the overall evaluation of the brand. Based on an analysis of the connection weights between neurons of the artificial neural network, the importance of different brand attributes for the brand evaluation is quantified. This results in concrete implications for brand management practice and potential for further investigations on the use of artificial intelligence in marketing analytics.

Keywords: artificial intelligence, brand management, image measurement, multilayer artificial neural network, connection weights, brand image, marketing analytics

INTRODUCTION

Brand image is one of the central constructs of brand management. It combines the various features that a consumer associates with a particular brand and thus significantly influences the purchase decision process (Esch & Langner, 2019a; Keller, 2005). Therefore, a brand image serves as a relevant behavioral science metric in monitoring the success of a brand (Esch & Eichenauer, 2017). Although it is referred to as a multidimensional attitudinal construct of the psyche (Meffert et al., 2019; Trommsdorff & Teichert, 2011), model building in the context of brand image measurement is commonly limited to simple arithmetic operations (Nufer, 2016; Trommsdorff, 1975).

The aim of this study is to investigate the use of artificial neural networks in this context of application in detail. This is because the use of artificial neural networks, as an essential method of artificial intelligence, let complex relationships be modeled automatically (Weber, 2020; Wennker, 2020). Thereby, this learning algorithm is intended to support the modeling of survey data, mapping non-linear and indirect connections between a brand and facets of its image. With the help of specific evaluation methods, the research will show ways to gain insight into the relationships generated in the artificial neural network

(Beck, 2018; Gajowniczek & Ząbkowski, 2020; Olden et al., 2004) and thus show the potential use of this learning algorithm for brand management.

BRAND IMAGE MEASUREMENT

Image represents a psychological variable of the human organism, which is interdependently influenced by the interaction of various variables and contributes significantly to a behavioral response (Kroeber-Riel & Gröppel-Klein, 2013). Within the framework of brand management, a brand image is defined as a multidimensional attitude construct in the mind of a consumer, which represents a compressed and evaluated image of a brand (Meffert et al., 2019; Trommsdorff & Teichert, 2011). A company can indirectly influence the brand image by means of brand management activities. However, the intended brand image of the management often differs from the actual brand image in the mind of the consumers. Hence, the image has to be measured, to gain insights into the consumers' perception of the brand (Burmann et al., 2018; Esch & Langner, 2019b).

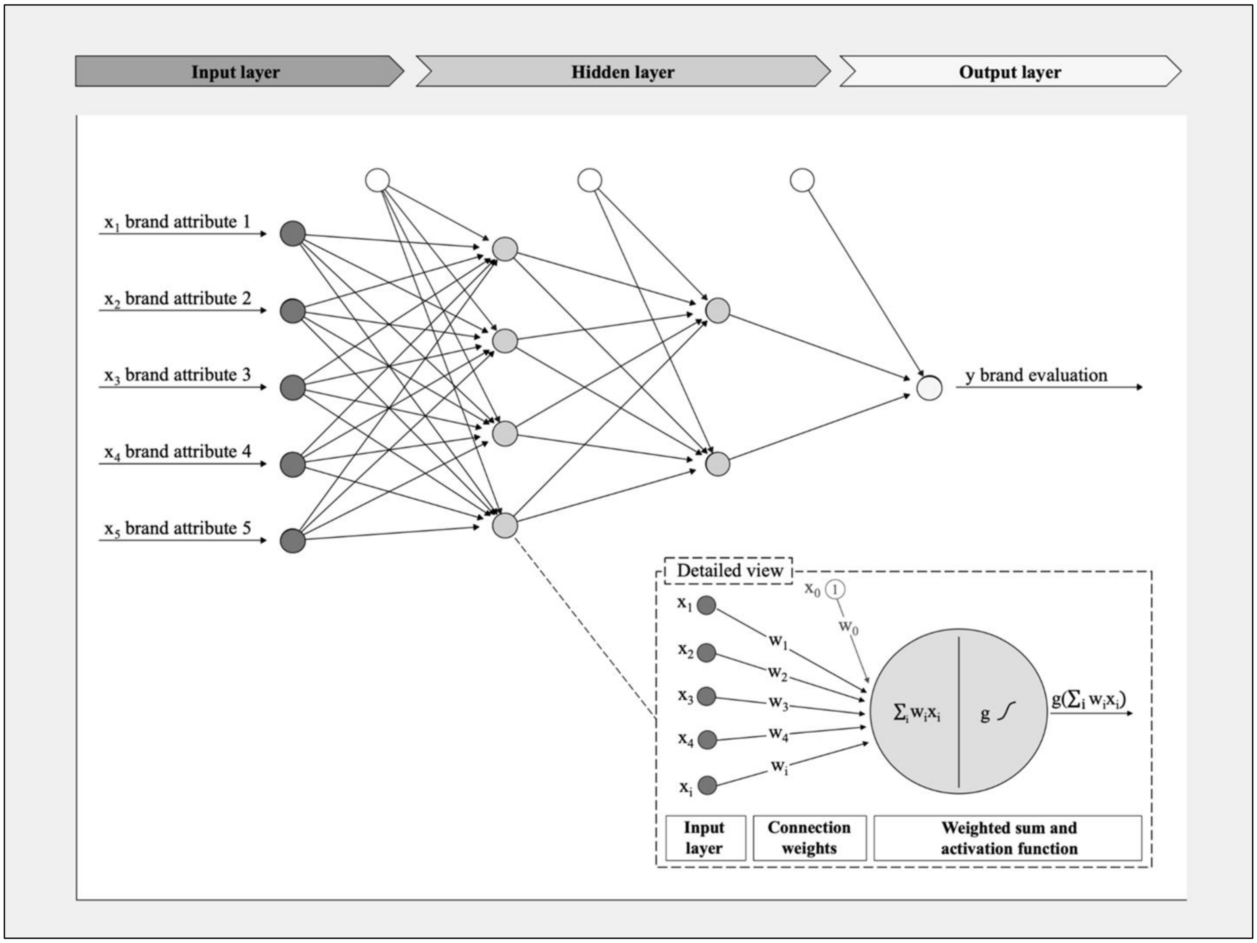
Based on the assumption that certain impressions of a brand in the mind of a consumer can be articulated (Bielefeld, 2012; Burmann et al., 2018), a survey can provide insights into the composition of the brand image. Although qualitative studies are thought to have certain advantages, the quantitative approach is of overriding priority in theory and practice. This is because quantitative studies yield results which are comparable and statistically generalizable (Keller, 2005; Nufer, 2002). Typically, consumers' brand image is measured as the attitude towards a brand. With the help of rating scales, the judgment of the entire brand as well as of separate attributes of the brand can be measured (Esch & Eichenauer, 2017). The subsequent model building is commonly based on simple arithmetic operations that assume a strictly linear or quadratic relationship, so it only roughly reflects the multidimensional and complex mechanisms in reality. For example, image formation does not always follow a linear functional relationship, whereby a changed evaluation of a brand attribute has a proportional effect on the evaluation of the brand as a whole (Nufer, 2016; Trommsdorff, 1975).

ARTIFICIAL NEURAL NETWORKS

A pioneering model of artificial intelligence – the artificial neural network – can open up new possibilities in this regard. It constructs learning processes with the help of mathematical functions conceptually based on processes in the human brain (Backhaus et al., 2018; Ernst et al., 2020; Kleesiek et al., 2020).

A common form of an artificial neural network is the multilayer perceptron. This allows the processing of a multitude of explanatory variables in an input layer, which is then related to one or more response variables in an output layer. These can be the evaluations of specific brand attributes associated with the brand evaluation (See Figure 1). The variables in an artificial neural network are mapped as circular neurons and linked by connection weights. An essential feature of this model is that there is a so-called hidden layer between the input layer and the output layer. Due to this hidden layer it is possible for the network to generate non-linear relationships (Backhaus et al., 2018; Dörn, 2018; Wennker, 2020).

FIGURE 1
SCHEMATIC REPRESENTATION OF AN ARTIFICIAL NEURAL NETWORK IN A BRAND CONTEXT



(adapted from Ernst et al., 2020)

To illustrate the principle of the hidden layer, the function of the neurons located in it is shown in detail in the figure. There, the values (x_i) coming from the input layer are each multiplied by their connection weights (w_i) and combined into a sum ($\sum_i w_i x_i$). However, this weighted sum is not simply passed on – which would lead to a concatenation of purely linear functions – but is given beforehand into a non-linear activation function (g). The latter is adjusted by the connection weight w_0, which has a fixed input value ($x_0 = 1$), and can be represented by various non-linear functions (such as a sigmoid function) depending on the network structure. Overall, this process combines all values of the input layer and transforms them non-linearly. The resulting output $g(\sum_i w_i x_i)$ is then sent to subsequent neurons, where the process is repeated (Ernst et al., 2020; Ramasubramanian & Singh, 2019).

In this way, the values emanating from the input layer – which can be represented, for example, by the evaluations of specific brand attributes – are passed through all neurons of the hidden layer and finally yield a result in the output layer. This result is a prediction about the response variable and is then compared with the actual value, for example, the brand evaluation. The difference between these two values is determined as an error. The connection weights are then adjusted backwards so that the total error is minimized across all data. During this process, known as backpropagation, the optimal connection weights are successively calculated, resulting in the final network model (Dörn, 2018; Ernst et al., 2020; Kleesiek et al., 2020; Weber, 2020).

The underlying principle of modeling differs from traditional approaches in key respects. This is because it is not necessary to make prior assumptions about correlations or to precisely define rules of calculation. Instead, a model is generated automatically by "learning" patterns and regularities directly from the data. This process is also commonly called machine learning (Döbel et al., 2018; Homburg, 2020). Machine learning is considered a key technology in artificial intelligence and has recently received a lot of media attention. This may be due, among other things, to the important successes of artificial neural networks in various problem areas. For example, artificial neural networks with a large number of neurons in the hidden layer are successfully applied in pattern recognition, image and language processing, and forecasting (Döbel et al., 2018; Dörn, 2018; Rebala et al., 2019).

THE USE OF ARTIFICIAL NEURAL NETWORKS TO MEASURE A BRAND IMAGE

Since artificial neural networks are considered a versatile and important method in various fields (Weber, 2020; Wennker, 2020), their potential for application in the context of brand image measurement will be analyzed below. Artificial neural networks can be used to approximate very complex relationships that can hardly be described with classical mathematical rules (Dörn, 2018), so there is no need to assume special dependency relationships when using this learning algorithm. Thus, artificial neural networks prove to be advantageous compared to approaches of brand image measurement that assume a purely linear or quadratic functional relationship. In addition, they can take many variables – even on different levels of scale – into account. This overcomes some limitations of other methods regarding the number and scale of variables (Backhaus et al., 2018; Günther & Fritsch, 2010).

One challenge in the context of artificial neural networks is the complex, partly opaque structure: "Even an ANN [Artificial Neural Network] able to make perfect predictions would tell us nothing about the functional form of the relationship" (Paruelo & Tomasel, 1997, p. 181 f.). To address this challenge and to increase the transparency of the relationships established or, as Beck (2018, p. 2) puts it, "[to] illuminate the black box", specific methods can be used. For example, it is possible to represent a network model graphically, to depict the individual connections and layers and thus to give an impression of its architecture (Beck, 2018). However, approaches that allow to investigate the contribution of variables in the artificial neural network are considered especially useful. Thus, the connection weights between the neurons of the artificial neural network can be evaluated, to make the contribution of input variables to the response variables quantitatively measurable (Beck, 2018; Gajowniczek & Ząbkowski, 2020; Olden et al., 2004). In this way, the methodological advantages of artificial neural networks can be exploited while extracting relevant information about the generated connections.

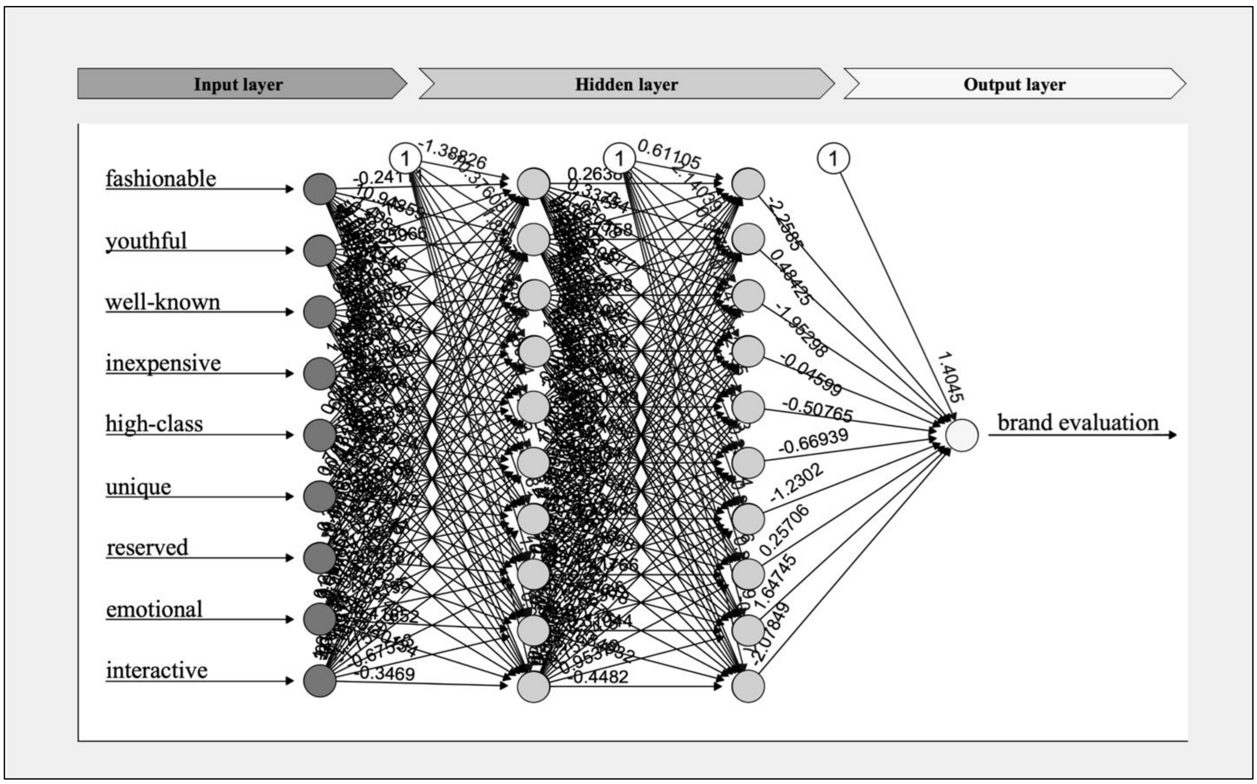
EMPIRICAL STUDY

The application of artificial neural networks to brand image measurement will be shown by means of an empirical study using the sportswear manufacturer adidas as a practical example. A quantitative image measurement based on a written survey using a standardized questionnaire can serve as the data set. On a six-point rating scale, the strength of specific brand attributes is firstly evaluated ("I think the adidas brand is..."). The image-relevant variables "fashionable", "youthful", "well-known", "inexpensive", "high-class", "unique", "reserved", "emotional", and "interactive" are addressed. In addition, the degree of affective attitude towards the brand is measured in form of the brand evaluation ("I evaluate the adidas brand overall...") from "very negative" to "very positive" (1-6). For the survey 1,353 respondents were interviewed once in various German cities, then after the respondents with at least one missing answer were removed, a sample of n = 1,101 was taken into account in the following data analysis.

Under the premise that the brand image – as the overall attitude of a consumer towards a brand – depends on the evaluation of specific attributes (Keller, 2005), an artificial neural network can be modeled between the evaluations of the brand attributes and the overall brand evaluation of adidas. In this study, the artificial neural network is generated using the programming language R (Günther & Fritsch, 2010; Ramasubramanian & Singh, 2019).

When creating models of artificial intelligence, it is common to train them with only a subset of the data, so the survey data are randomly subdivided and the artificial neural network is trained with 80% of them ($n_{train} = 881$). An additional 10% of the survey data ($n_{validate} = 110$) is then used to adjust certain network characteristics, such as the number of hidden layers and the number of neurons within them. Adjusting these so-called hyperparameters is meant to optimize the models' accuracy. In the present case, this step results in the artificial neural network shown in Figure 2 with ten neurons each in two hidden layers. This network is then tested by using the remaining 10% of the survey data ($n_{test} = 110$). From this subset, only the respondents' evaluations of the brand attributes are entered into the artificial neural network, then on this basis, a prediction about the overall brand evaluation is generated. This predicted brand evaluation matches the actual brand evaluation of the respondents in 68.18% of the cases. The model testing is intentionally performed on data not formerly used to train the artificial neural network, to ensure that the model has established generalizable relationships (Ernst et al., 2020; Kleesiek et al., 2020; Ramasubramanian & Singh, 2019).

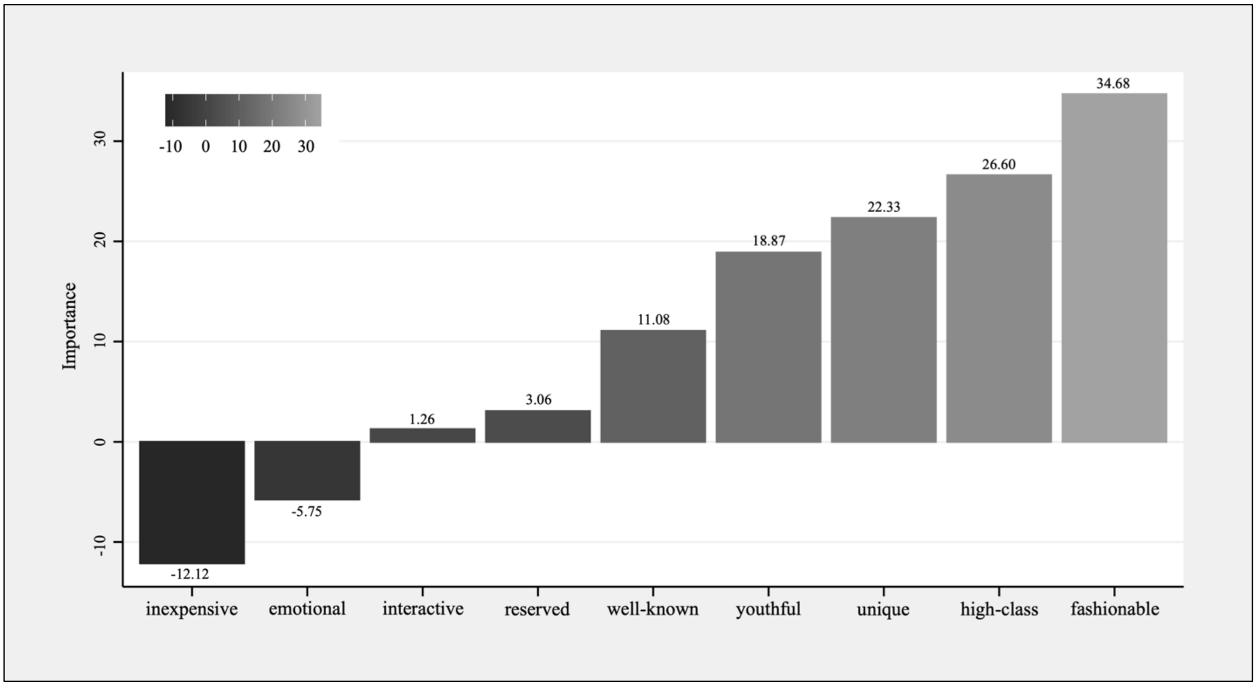
FIGURE 2
AN ARTIFICIAL NEURAL NETWORK EXEMPLIFIED EMPIRICALLY BY THE BRAND IMAGE OF ADIDAS



The network model shown can give an impression of the structure of the specific artificial neural network, but the purely graphical representation makes it difficult to interpret the relationships generated (Beck, 2018). To obtain quantitatively measurable insights into the importance of the brand attributes, the model connections are analyzed. For this purpose, the product is calculated of the raw input-hidden and hidden-output connection weights and summed across all hidden neurons. This procedure is performed between every input neuron and output neuron (Olden et al., 2004). The result provides information about the magnitude and sign with which the individual brand attributes (input neurons) are connected with the brand evaluation of adidas (output neuron) in the artificial neural network (Gajowniczek & Ząbkowski, 2020; Olden et al., 2004). The computation is performed using an algorithm implemented by Beck (2018).

The bar chart below (See Figure 3) illustrates the calculated importance of the variables in the network model.

FIGURE 3
THE VARIABLE IMPORTANCE EXEMPLIFIED EMPIRICALLY BY THE BRAND IMAGE OF ADIDAS



According to the evaluation of the connection weights, seven of the nine brand attributes show a positive connection with the brand evaluation of adidas. The brand image measurement suggests that "fashionable", followed by "high-class", "unique" and "youthful" are the most pronounced ones. These four brand attributes show a particularly strong positive connection with the brand evaluation of adidas. By contrast, the brand attributes "interactive" and "reserved" appear to have a lower importance on the basis of the survey data. Furthermore, a negative connection can be observed for "inexpensive" and "emotional". According to the calculated importance of the variables, a pronounced association of the brand with these two attributes has a negative impact on brand evaluation.

DISCUSSION

From the results of the empirical analysis, several recommendations for corporate practice can be derived: One evident implication is the increase of brand management activities strengthening the brand attributes identified as positive for brand evaluation in the artificial neural network. The results of the analysis suggest that the attributes "fashionable", "high-class", "unique" and "youthful" should be highlighted in the sportswear manufacturer's brand communication. With the aim of optimizing the brand evaluation, it seems advisable to focus on these brand attributes rather than on the brand attributes showing a low positive importance such as "interactive" and "reserved".

In addition, the results let conclusions be drawn about the price positioning of the adidas brand. The positive association of "high-class" in combination with the negative association of "inexpensive" suggests a generally higher-value brand positioning for adidas. These basic assumptions, derived from the evaluation of the connection weights, can serve as a systematic basis and can be specifically targeted in additional studies. For example, the identified negative importance of the brand attribute "emotional" could be systematically further investigated. Based on this, there is the potential to examine to what extent an opposite attribute like "informative" is positively connected with the brand evaluation.

CRITICAL REFLECTION

For a critical reflection of the presented application of artificial neural networks in the context of brand management, two central aspects call for special consideration. Firstly, the approach requires a deeper discussion of the requirements for brand image measurement, and secondly, it necessitates a more detailed discussion of the technical requirements.

With regard to the survey design chosen here, Esch and Eichenauer (2017) point out that the full scope of the inner brand image cannot be captured by querying predefined attributes, so the extent to which an inclusion of more brand attributes contributes to a more differentiated result and the extent to which attributes not predefined can be processed in an artificial neural network need to be further examined. With regard to the technical aspects, there is a need for not only the necessary infrastructural conditions but also the appropriate technical expertise (Dörn, 2018; Weber, 2020). In general, creating an artificial neural network is more challenging than is creating a traditional statistical model and interpreting it is more complicated (Beck, 2018). However, traditional statistical models usually represent the real dependency relationships of consumers' behavior to only a limited extent – especially if based on the assumption that functional relationships are linear (Meffert et al., 2019). In view of this, Meffert et al. (2019) state that for the non-linear interdependencies typical in marketing decision-making, there are so far no algorithms offering a satisfying solution.

The present approach, illustrated by the empirical example of the sportswear manufacturer adidas, is meant to meet this challenge. It lets modeling be non-linear and multilayered and, by analyzing the connection weights, lets practical implications be derived. The extraction of information about the structure of artificial neural networks should ultimately increase their application potential in areas such as brand management. For example, this learning algorithm can be applied especially to very large data sets, whose size is significantly greater than the size of the survey data used. Further discourse is recommended regarding the potential of artificial neural networks for operational brand management practice. Moreover, validation of the proposed concept – also in a cross-industry context – is being sought.

CONCLUSION

This research paper began with a brief introduction to the fundamentals of brand image measurement and of artificial neural networks then presented a conceptual connection between both subjects. The possibilities arising from the use of artificial neural networks for brand image measurement were illustrated by an empirical study using the brand of the sportswear manufacturer adidas as an example. A quantitative survey evaluating specific brand attributes, as well as the overall brand evaluation of adidas, served as the data set. Based on this, a multilayer artificial neural network was created and the connection weights between neurons were evaluated. In the context of brand image measurement, this procedure is intended to gain insights into the underlying connection between specific brand attributes in brand evaluation.

This study offers reasons for continuing to explore the extent to which algorithm-based approaches from computer science, such as the learning methods of artificial intelligence, can serve to enrich academic and practical issues in marketing and management. The associated approaches sometimes offer a useful complement to the methodology established in many studies – a methodology characterized by the traditional tools of univariate and multivariate analysis (Homburg, 2020). The range of artificial intelligence methods available in this context extends far beyond the artificial neural networks described above (Döbel et al., 2018; Ramasubramanian & Singh, 2019; Rebala et al., 2019), so apparently the possibilities for brand management have not yet been fully exhausted and should be examined more comprehensively in future. The use of artificial neural networks in the context of brand image measurement, as presented here, is only one of these possibilities.

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