Quantifying Differences Between Architects' and Non-architects' Visual Perception of Originality of Tower Typology Using Deep Learning

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Abstract. The paper presents a computational methodology to quantify the differences in visual perception of originality of the rotating tower typology between architects and non-architects. A parametric definition of the Absolute Tower Building D with twelve variables is used to generate 250 design variants. Subsequently, sixty architects and sixty non-architects were asked to rate the design variants, in comparison to the original design, on a Likert scale of 'Plagiarised' to 'Original'. With the crowd-sourced evaluation data, two neural networks - one each for architects and non-architects - were trained to predict the originality score of 15,000 design variants. The results indicate that architects are more lenient at seeing design variants as original. The average originality score by architects is 27.74% higher than the average originality score by non-architects. Compared to a non-architect, an architect is 1.93 times likelier to see a design variant as original. In 92.01% of the cases, architects' originality score is higher than non-architects'. The methodology can be used to quantify and predict any subjective opinion.

Keywords: Originality · Tower typology · Visual perception · Crowd-sourced · Subjective evaluation · Deep learning · Neural network

1 Introduction

Architecture is a unique discipline where art and engineering meet subjective demands. Architects offer design solution to their clients (predominantly non-architects), but these two groups may not always have the same aesthetic sensibilities. Multiple studies [1–3] have shown that architects and non-architects have different preferences. Jeffrey and Reynolds [4] studied the differences in aesthetic "code" of architects and non-architects, and argued that buildings constructed according to the "code" of architects is less likely to receive popular acclaim. Another study [5] focused on the decision-making in purchasing residential properties. It found that non-architects ranked a property perceived as "family home" higher than a property perceived as "light and outward facing". This finding indicates that subjective factors tend to be more relevant to non-architects than

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objective design goals. Moreover, Brown and Gifford [6] concluded that typically, architects cannot predict the non-architect's aesthetic evaluation of architecture. Therefore, a potential conflict exists between architects and non-architects, who may have different expectations from a building. This research investigates the differences between architects and non-architects with regard to the visual perception of originality of design of the tower typology.

Fig. 1. Absolute tower d on the right. Clicked by Sarbjit Bahga, reproduced under CC license.

Throughout the history of architecture, the tower typology has been a symbol of power and wealth, the identity of city skylines, and iconoclastic landmarks for human navigation [7]. In many ways; by combining vertical mobility, material innovation, mechanical heating, speed of construction, wind and earthquake resistance, evacuation planning, and service automation [8]; towers (or skyscrapers) exhibit the pinnacle of architectural and engineering design [9]. During the design of a tower, architects are progressively moving away from the extruded box towards non-orthogonal designs [10]. Simple shapes such as rectangle and ellipse are often transformed and varied in the z-axis to conceive complex geometries. Vollers [10] explains *that: "Twisted geometries with repetition of elements are applied not so much for economic gain as for semiotic connotation"*.

This research uses the design of Absolute Tower D designed by MAD Architects (see Fig. 1) - a twisting tower with elliptical floor plan [11] - as the original design against which architects and non-architects are asked to evaluate the originality of design variants. The following sections elaborate the background, the research methodology, the use of deep learning for quantification, the results, and the future scope of work.

2 Background

2.1 Originality in Design

The definition of originality in the context of design is rather subjective and open-ended. It is often conflated with innovation, novelty and creativity. Being innovative, novel and/or creative independently may not necessarily mean that a design, a work of art, a theory, or a discovery is original. The phenomenon of simultaneous invention explains that most scientific advancements are made independently and more or less simultaneously by multiple scientists [12], exemplified as early as in 1774 by the simultaneous discovery of oxygen by Scheele and Priestley. In the context of art, Lamb and Easton [13] have argued that science and art are not dissimilar in this regard. The way papers of simultaneous discoveries are same in terms of the core idea, but not same word-for-word; likewise, two painters may independently paint about the same core theme, but their paintings may not be identical stroke-for-stroke. Therefore, originality cannot be independently absolute. It can only be reviewed in comparison to reference(s). Since originality is relative, being innovative, novel and/or creative cannot be linked causally to originality. Instead, they are better understood as features of originality.

The emphasis on originality and individuality as a way of life has been propagated by popular ad campaigns in the twentieth and twenty-first centuries; exemplified by Apple's 1997 ad campaign slogan "Think different". Reinartz and Saffert [14] studied 437 ad campaigns and concluded that the combination of originality and elaboration is the most effective way (96% more than median) to inspire people to view a product favourably and buy it. It is followed by the combination of originality and artistic value (89% more than median). It would be safe to conclude that the perception of originality - be it visual, audio, tactile, or spatial – subliminally plays a significant role in one's appreciation of a product or an act of creativity. However, a universal definition of originality in the context of design is difficult to establish because of the fact that originality in design can be discerned in several ways – in the process, function, and form. Originality of a process may be defined as a byproduct of creativity that makes an idea evolve into a system and then into an artefact [15]. Originality may be sought in the function of a design which typically manifests itself through transformation of scientific or technical research into a product [16]. Originality may also be sought in the form of a design. Often times form is explored with structural performance [17] and/or energy performance [18] in mind. Originality may also accessed as an antonym of plagiarism, i.e., from the perspective of copyright laws. However, existence of copyright laws, their structure (state vs federal), and the extent of the law's ambit varies from one country to the other. The processes to detect and the legal implications of violating originality (or copyright) of design are beyond the scope of this research.

Non-architects are typically not privy to the process of architectural design. Their sense of originality in architecture is primarily derived from visual stimuli [19]. The aim of this research is to compare the visual perception of originality between architects and non-architects. In other words, this research aims to quantify the originality of forms. Evaluating the originality of a given form without an explicit reference would require the evaluator to subliminally conjure all the forms ever seen, and then compare the given form with the conjured forms that act as reference. Therefore, understanding originality of form, similar to understanding the originality of scientific discoveries, is an exercise of (visual) comparison with one's experiences as the reference. For the purpose of this research, instead of relying on visual comparison with the sub-conscious, forms of design variants will be compared to the form of the original (reference) design of the Absolute Tower D.

It is to be noted that non-architects associated with other design fields may understand architecture beyond visual stimuli. It may be argued that "non-architect designers", as a group, sits between "architects" and "non-architects non-designers", with respect to holistic understanding of the process of architectural design. In the context of this paper, the phrase "non-architect(s)" excludes the sub-group of people that are associated with any design field – both as context and in selection of participants for evaluation of originality.

2.2 Machine Learning in Architecture

Artificial intelligence, and in particular machine learning, has become a popular topic in all computational processes across industries. Since the 2010s it has been incorporated in various researches in architectural design as well. Machine intelligence can be utilised to support creativity [20], automate housing layout generation [21], automate implicit design iteration through discretisation [22], transfer 3D style of a geometry to another geometry [23], appropriate performance simulation [24], and calculate urban space perception [25].

Traditional programming requires the programmer to explicitly define rules to (subsequently) generate output. Deep learning is a departure from such a system. It is a subset of machine learning that uses deep neural network with multiple hidden layers to statistically appropriate the entire solution space (see Fig. 2). It does so by training on discrete sample dataset with known input variables (independent variables or features), and known output (dependent variable(s) or label(s)). On completion of training, i.e., after statistically mapping the relationship between the independent and dependent variables (see Fig. 2b), the neural network is capable of predicting output for any new set of input variables. Consequently, with the use of deep learning, the number of data samples that need to be explicitly evaluated by survey participants reduces significantly (from thousands to hundreds). The evaluation of additional data samples can subsequently be predicted with a neural network that is trained with the explicit evaluations (see Fig. 2c).

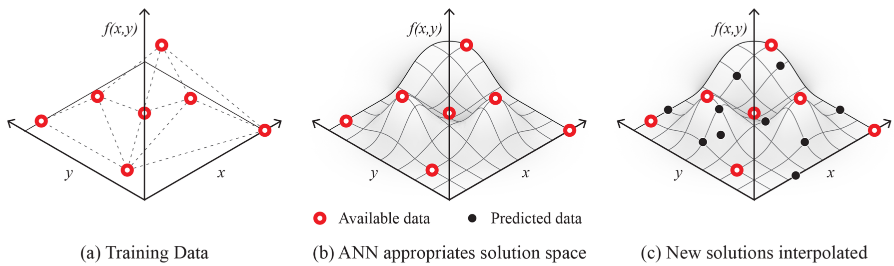


Fig. 2. Training and prediction by neural network

3 Research Methodology

This research uses a computational methodology that can be used to quantify (see Fig. 3) and predict any kind of subjective evaluation of design. The methodology combines crowd-sourced design evaluation with the statistical power of deep learning. The methodology has four key steps mentioned as following –

1. *Defining design variants*: The first step in the process is to collect or generate design variants that can be evaluated. For example, if urban streetscapes are to be evaluated for beauty, images of urban streetscapes need to be collected for evaluation. If a parametric definition is being used for design, design variants need to be generated by varying the parameters (independent variables).
2. *Crowd-sourced evaluation*: The second step in the process is to get the design variants evaluated by relevant group(s). The evaluation data is discrete in nature and does not truly represent the solution space (see Fig. 2a). Therefore, it is not directly used for comparative study.
3. *Neural network training*: The third step in the process is to train a deep neural network with the evaluation data (output or dependent variable) and the design parameters (input or independent variable) that define the design variants. Through training, the neural network learns to appropriate the solution space (see Fig. 2b).
4. *Predicting subjective evaluation*: On the completion of training of the neural network with sufficient accuracy, the fourth step is to predict subjective evaluations of a larger new set of design variants. Since neural networks learn the solution space during training, they can predict the evaluation of new variants by virtue of interpolation (see Fig. 2c). Finally, the predicted values are used for comparative analysis.

The following sub-sections discuss the four steps in detail with respect to this research, along with discussing the preliminary analysis of the evaluation data and the limitations in the process of quantification.

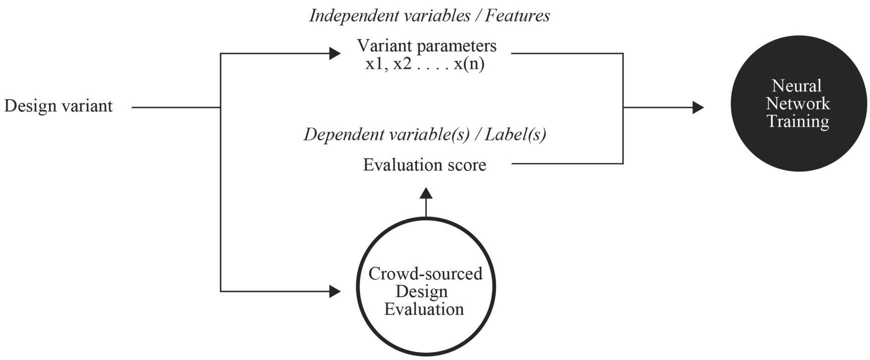


Fig. 3. Computational methodology for training a neural network to quantify and predict crowd-sourced subjective evaluation.

3.1 Step 1: Defining Design Variants

Design variants of Absolute Tower D were defined and generated by a parametric Grasshopper definition of the original design. The original design [11] can be parametrically represented by only five parameters – the two radii of the elliptical floor plan, total number of floors, floor to floor height (or total height) and total rotation (or floor to floor rotation). In order to have design variants of similar visual weightage, total number of floors and floor to floor height are not varied to generate design variants. In addition to the three other parameters of the original design, nine additional parameters are added to the parametric definition. These additional parameters change the shape of the floor plan from ellipse to a four-legged star to a square and to a rhombus, control the nature of the rotation of floor plates (linear or bezier), change the state of the balconies (present or absent), and scale the floor plates towards the top and the bottom of the tower. The floor plan is represented by a NURBS curve instead of an ellipse, and the corner point weights of the control polygon and the position of the mid-points of the control polygon are varied to morph the floor plan into the four shapes. The parameters (see Table 1) are elaborated as following -

- *(x1) Radius 1 of the floor plan (plan_r1)*: Controls the length of the bounding box of the floor plan. When the floor plan is elliptical, it represents one of the radii of the ellipse.
- *(x2) Radius 2 of floor plan (plan_r2)*: Controls the width of the bounding box of the floor plan. When the floor plan is elliptical, it represents one of the radii of the ellipse.
- *(x3) Floor plan corner point weight (crpt_weight)*: Controls the weightage of the corner points of the control polygon of the floor plan. When all the other parameters are kept constant at the values of the original design, *crpt_weight* = 0.0 yields a rhombus floor plan, *crpt_weight* = 0.5 yields the original design, and *crpt_weight* = 1.0 yields a rectangular floor plan (see the first row in Fig. 4).
- *(x4) Floor plan mid-point movement (midpt_move)*: Controls the displacement of the mid-points of the control polygon of the floor plan towards the centre of the floor plan. When all the other parameters are kept constant at the values of the original design, *midpt_move* = 0.0 yields the original design, and *midpt_move* = 1.0 yields a blunt four-legged star floor plan (see the second row in Fig. 4). When all parameters except *crpt_weight* and *midpt_move* are kept constant at the values of the original design, *crpt_weight* = 1.0 and *midpt_move* = 0.5 yield a sharp four-legged star floor plan (see the third row in Fig. 4).
- *(x5) Total rotation (tot_rot)*: Controls the total angle of rotation between the bottom and the top floor plates.
- *(x6–x9) Distribution of the rotation values (rotstart_x, rotstart_y, rotend_x, rotend_y)*: The four parameters control the nature of the distribution of the rotation values of floor plates. The distribution is calculated by a bezier S-curve. Therefore, the four parameters are the two anchor points (*rotstart_y* and *rotend_y*) and the two handles (*rotstart_x* and *rotend_x*) of the S-curve. When all of the four parameters have a value of zero, the S-curve takes the shape of a straight line, thereby making the distribution linear in nature.

- *(x10) Presence or absence of balcony (bal_state)*: Controls the presence or absence of balcony projections using a discrete boolean value. When *bal_state* is zero, the balconies are replaced by glazed facade.
- *(x11–x12) Scaling values of the floor plates (scale_top, scale_bottom)*: Controls the amount of scaling in the top three quarters (*scale_top*) and the bottom quarter of the tower (*scale_bottom*). The scaling of the floor plates start from the top of the bottom quarter towards both the directions.

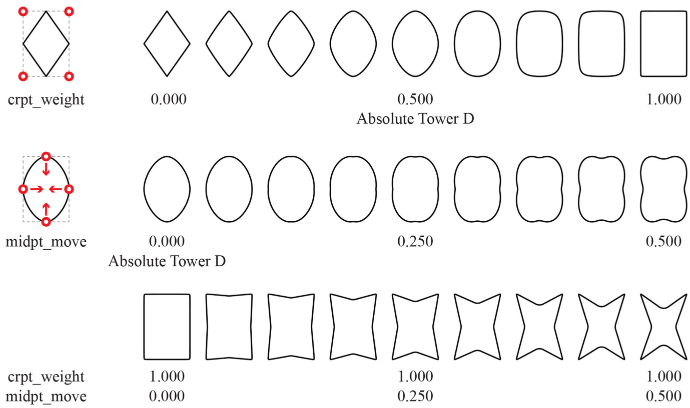


Fig. 4. Variation in floor plan with *crpt_weight* and *midpt_move*

Table 1. Domains of the parameters (independent variables) of the design variants.

Parameters	Minimum	Maximum	Tower D	Number of possible values
plan_r1	10.00	15.00	13.70	500
plan_r2	15.00	25.00	18.50	1000
crpt_weight	0.000	1.000	0.500	1000
midpt_move	0.000	0.500	0.000	500
tot_rot	0	720	208	720
rotstart_x	0.000	0.750	0.535	750
rotstart_y	0.000	0.750	0.000	750
rotend_x	0.000	0.750	0.395	750
rotend_y	0.000	0.750	0.000	750
bal_state	0	1	1	2
scale_top	0.010	1.000	1.000	990
scale_bottom	0.500	1.000	1.000	500

In multivariate studies such as this research, the minimum number of data samples needed to train a neural network can be determined using few industry accepted rules of thumb. Sekaran and Bougie [26] prescribe the 10x rule which states that the number of data samples should be at least ten times the number of independent variables. To test the correlations of independent variables, Green [27] recommends a minimum sample size of 50 + 8k, where k is the number of independent variables. To conclusively make predictions, Green [27] recommends a minimum sample size of 104 + k, where k is the number of independent variables. Given that the number of independent variables is twelve in this research, the rules of thumb recommend a minimum of 120, 146 and 116 data samples respectively. To accommodate additional testing data to measure the accuracy of neural network, this research has used 250 data samples (design variations) for crowd-sourced evaluation. Figure 5 shows 84 out of the 250 design variants.

3.2 Step 2: Crowd-Sourced Evaluation

The second step in the process of quantifying subjective evaluations is to evaluate the design variants. To facilitate interpolation of the extreme cases, fifty of the 250 design variants were generated by combining the minimum, maximum and original design values of the independent variables. The rest of the 200 design variants were generated using random values. Similar to the calculation of minimum number of data variants needed for evaluation, the minimum number of participants needed in the process of evaluation also needs to be ascertained. As a rule of thumb, Clark and Watson [28] recommend ten participants per item on the rating scale, whereas DeVellis [29] recommends fifteen participants per item on the rating scale. This research has used a Likert scale of four items for crowd-sourced evaluation. Thus, following the latter rule of thumb, sixty participants were needed for evaluation. Since this research compares the evaluations of two groups, i.e., architects and non-architects, the 250 design variants are evaluated by sixty architects as well as sixty non-architects. The lowest age amongst the architects was 23. Consequently, all the selected non-architect participants were older than 22. As mentioned in Sect. 2.2 “Originality in Design”, the non-architect participants exclude people associated with other design fields. The quantification of the visual perception of originality of the excluded sub-group is not part of this research.

Since the evaluations are comparative in nature, to acquaint the participants to the extremities of the design variants, all the design variants were shown to each of them before the process of evaluation. The architects and the non-architects were asked to rate the design variants against the following question –

“How would you rate the visual relationship of the displayed designs with respect to the reference design?”

A Likert scale was used to collect the evaluations. The design of a Likert scale has two variables – the number of categories in the scale and the description of the categories in the scale. Given that 250 design variants were to be evaluated, six or above categories could lead to decision fatigue [30]. A four-category scale was selected over a five-category scale to reduce the risk of participants avoiding the process of evaluation by selecting the ‘Neutral’ category. Agree-disagree descriptions yield lower quality data as they suffer from acquiescence response bias [31]. Therefore, qualitative labels of ‘Plagiarised’, ‘Similar’, ‘Different’, and ‘Original’ were used as categories.

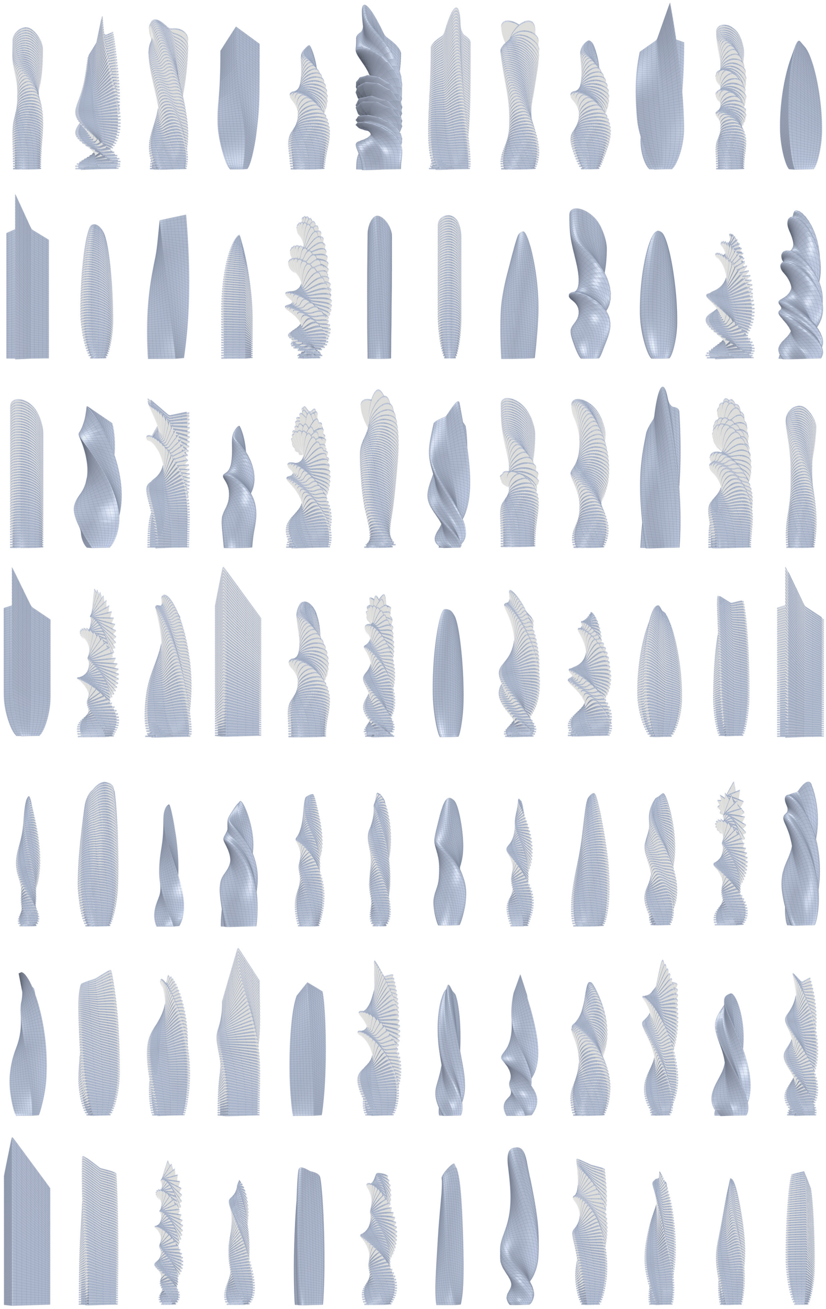


Fig. 5. 84 of the 250 design variants used for crowd-sourced evaluation; top left is the original design, bottom left is a rectangular extrusion variant without balcony.

The design variants were shown alongside the reference design (original design). The order of the design variants was randomised for each participant. The participants were not informed that the design variants are derived from a universal parametric representation. This information was skipped to understand the visual perception of originality of the design variants as an explicit artefact, without any connection to the process of generation of the design variants. Parametric representation may be self-evident to some of the participating architects. The quantification of the difference in visual perception of originality between architects that recognise the underlying parametric logic and architects that do not recognise the underlying parametric logic is not part of this research.

For every design variant i, the originality score is calculated by Eq. 1 as follows -

$$\text{Originality score}_{(i)} = \left(\sum_{n=1}^{r} L_{(i)(n)} \times W\right) / r \tag{1}$$

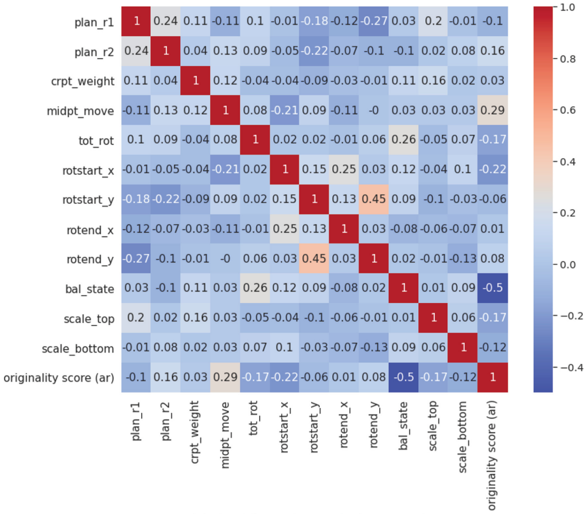
where,

i = Design variant identifier
r = Number of Likert evaluations per design variant
L = Likert evaluation
L = Likert evaluation
W = 0.00, if $L_{(i)(n)}$ is ‘Plagiarised’
0.33, if $L_{(i)(n)}$ is ‘Similar’
0.67, if $L_{(i)(n)}$ is ‘Different’
1.00, if $L_{(i)(n)}$ is ‘Orginal’

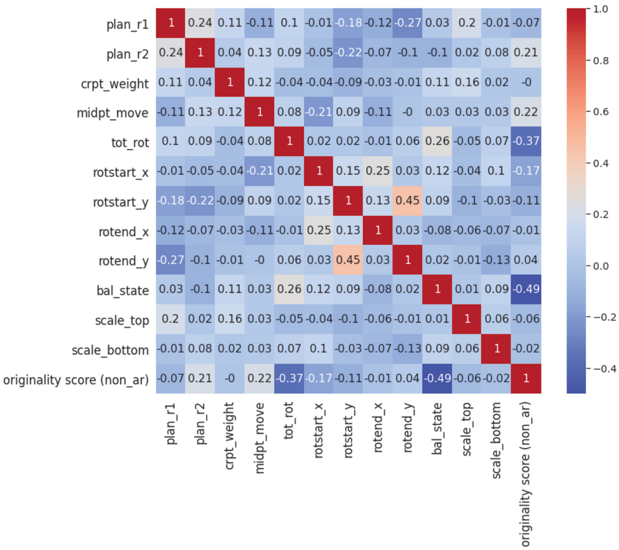
If all the evaluations of a design variant are ‘Plagiarised’, the originality score of the design variant becomes 0. If all the evaluations of a design variant are ‘Original’, the originality score of the design variant becomes 1. In other words, originality score of 0 implies that the particular design variant is visually perceived as ‘Plagiarised’ by everyone, and originality score of 1 implies that the particular design variant is visually perceived as ‘Original’ by everyone. Each design variant has two originality scores – one for architects (*Originality score (ar)*) and one for non-architects (*Originality score (non_ar)*). As a result, two tables (one each for architect’s and non-architect’s originality scores) of data with 250 rows and thirteen columns were compiled to train two neural networks. The rows represent the design variants. The first twelve columns represent the independent variables that define the design variants. These are common for both the tables. The last column stores the respective dependent variable, i.e., the originality scores of the respective design variants by architects in one and by non-architects in the other.

3.3 Preliminary Analysis of Evaluation Data

Correlation matrices (see Fig. 6) were generated to understand the intra-relationships between all the variables (independent and dependent). Depending on the correlation values, independent variables are excluded from deep learning. Additionally, the correlation values indicate which independent variables play a major role in the visual perception of originality.



(a) Architects' correlation matrix

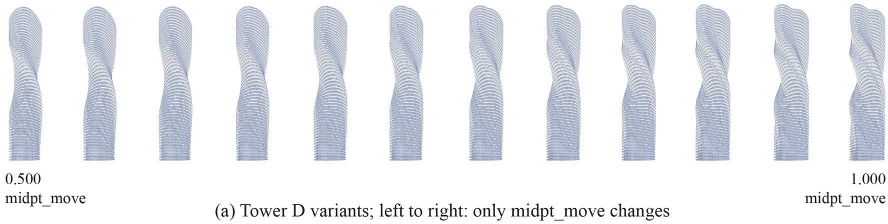


(b) Non-architects' correlation matrix

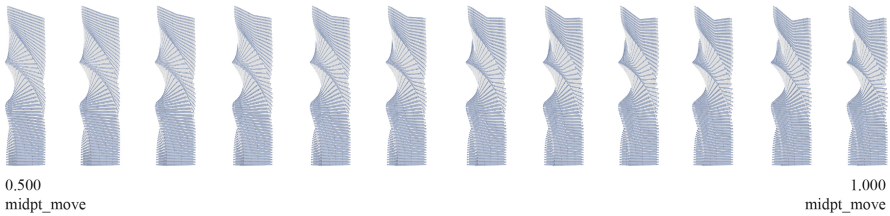
Fig. 6. Intra-correlation matrices of all variables in crowd-sourced data

Exclusion of Independent Variables. Independent variables with high intra-correlation ($r > 0.75$) are typically excluded from training neural network because they tend to supply the same information to the neural network. Consequently, by including both the independent variables, one adds noise instead of incremental information. As the colour-coded matrices reveal, none of the independent variables have high intra-correlation ($r > 0.75$). Therefore, all the independent variables are to be included in the training. Additionally, none of the independent variables have high correlation ($r > 0.75$) to either of the dependent variables. This is a typical feature of data sets that are compiled from subjective observations. The lack of strong correlation makes it almost impossible for traditional statistical methods to appropriate such a data set with a high degree of accuracy (~75% or above).

Significant Independent Variables. The analysis of the correlations of the independent and the dependent variables (see Table 2) reveals that seven out of the twelve independent variables are inversely correlated to the dependent variables. Floor plan mid-point movement (*midpt_move*) exhibits highest correlations with the originality scores of architects (r = 0.29) and non-architects (r = 0.22). As shown in Fig. 7 (see Fig. 4 for 2D plans), this independent variable changes the shape of the plan from an ellipse to a four-legged star.



(a) Tower D variants; left to right: only midpt_move changes



(b) Tower D variants with crpt_weight = 1.000; left to right: only midpt_move changes

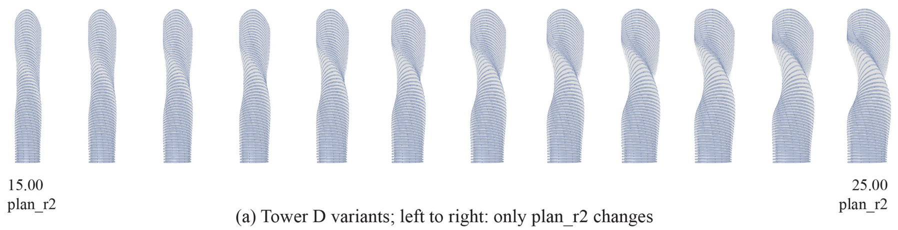
Fig. 7. Visual effect of varying *midpt_move* on the 3D of tower D

Radius 2 of floor plan (*plan_r2*) exhibits the second highest correlations with the originality scores of architects (r = 0.16) and non-architects (r = 0.21). As shown in Fig. 8, this independent variable controls the horizontality of design variants, thereby reducing slenderness with increase in value. The nature of the two independent variables with highest correlations with dependent variables (*midpt_move* and *plan_r2*) indicates that when visually comparing towers (or design variants) of the same height, both architects and non-architects tend to subliminally concentrate more on visual features that horizontally control the overall silhouette of the towers.

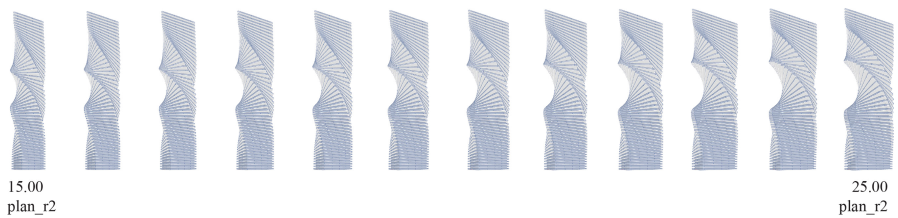
Presence or absence of balcony (*bal_state*) has the highest inverse correlations with the originality scores of architects (r = −0.50) and non-architects (r = −0.49). Additionally, it exhibits the lowest absolute difference in correlations ($|\Delta r| = 0.01$) between architects and non-architects. This suggests that when visually comparing towers for originality (or plagiarism), both architects and non-architects tend to ignore features that affect local surface articulation (see Fig. 9).

Table 2. Correlations of independent and dependent variables in crowd-sourced data.

Independent variables	Originality score (ar)	Originality score (non_ar)	Absolute difference
plan_r1	−0.10	−0.07	0.03
plan_r2	0.16	0.21	0.05
crpt_weight	0.03	0.00	0.04
midpt_move	0.29	0.22	0.07
tot_rot	−0.17	−0.37	0.20
rotstart_x	−0.22	−0.17	0.05
rotstart_y	−0.06	−0.11	0.05
rotend_x	0.01	−0.01	0.02
rotend_y	0.08	0.04	0.04
bal_state	−0.50	−0.49	0.01
scale_top	−0.17	−0.06	0.11
scale_bottom	−0.12	−0.02	0.10

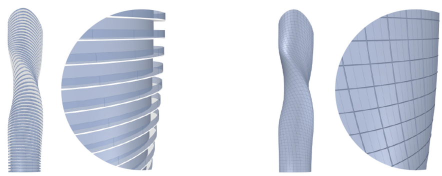


(a) Tower D variants; left to right: only plan_r2 changes



(b) Tower D variants with crpt_weight = 1.000; left to right: only plan_r2 changes

Fig. 8. Visual effect of varying *plan_r2* on the 3D of tower D



(a) Tower D variant (bal_state = 1) (b) Tower D variant (bal_state = 0)

Fig. 9. Visual effect of varying *bal_state* on the 3D of tower D

Total rotation (*tot_rot*) exhibits the highest absolute difference in correlations ($|\Delta r|$ $= 0.20$) between the originality scores of architects ($r = -0.17$) and non-architects ($r = -0.37$). This would appear to indicate that architects tend to be more visually sensitive towards rotation of floor plates. Conversely, non-architects tend to see rotated towers as a visually homogeneous group without much regard to finer differences in the amount of rotation.

3.4 Steps 3 and 4: Neural Network Training and Predicting Originality Score

The third step in the process of quantifying subjective evaluations using deep learning is to train a neural network with the evaluation data. On the completion of training of the neural network with sufficient accuracy, the fourth step is to predict subjective evaluations of a larger set of design variants.

Google Colab was used to write, edit and execute the code for steps 3 and 4. Scikit-learn machine learning library was used for greater flexibility and control over the neural network models. Choosing the hyper-parameters of a neural network (e.g., the number of hidden layers, the number of neurons in each layer, activation function, loss function, batch size, and number of epochs) is a complex process, that affects the network's efficiency. Scikit-learn's 'GridSearchCV' class was used to iteratively train the two neural networks with varied hyper-parameters, until best results were attained.

The two neural networks were trained on 200 design variants. The effectiveness of the two neural networks was tested on the remaining fifty design variants. The select neural network model for architects can predict originality score of design variants with root mean square error of 0.08, R2 score of 0.81 and accuracy of 91.35%. The select neural network model for non-architects can predict originality score of design variants with root mean square error of 0.07, R2 score of 0.83 and accuracy of 90.04%.

As part of step 4, the two trained neural networks were used to predict the originality scores of 15,000 design variants. The values of the independent variables required to generate the 15,000 design variants were calculated by combining equidistant interpolation of the domains of each independent variable. Finally, the 15,000 originality scores by architects as well as non-architects were tabulated to quantify the differences.

3.5 Limitations of Quantification

Each step of the methodology and each aspect of each step of the methodology have intrinsic as well as extrinsic limitations which may affect the quantification of the originality scores. Given the variance in absolute differences between the correlations of independent and dependent variables between architects and non-architects (see Table 2), changes in the selection of parameters to be varied and the range in which they are to be varied to generate the design variants will yield different originality scores. The form used in step 2 of the process, i.e., collection of crowd-sourced evaluation has intrinsic limitations. Changing the perspective from which design variants are seen in the form, and changing the medium of seeing the design variants (rendered, diagrammatic, pictures of model, animated, vs mounted on VR set etc.) will affect the visual perception of objects or buildings. Collection of such comparative data sparks questions about the extrinsic influences, e.g., is the visual perception of architecture by non-architects who are either designers or are trained in artistic fields more correlated to architects instead of non-architects not trained in creative fields? Additionally, the data used to train the neural networks is reflective of the socio-cultural bias of the volunteers. This feature of the nature of crowd-sourced data can be utilised to analyse and predict design preferences specific to groups of people (see section "Conclusion").

4 Result and Discussion

The percentage distribution of the originality scores of 15,000 design variants by architects as well as non-architects are shown in Fig. 10 through ten bins with bin-width of 0.10. Table 3 shows the numerical summary of the predicted originality scores. To understand the nature of the respective originality scores, Fig. 10 and Table 3 are to be read in conjunction. The nature of the percentage distribution bins indicates two differentiators between architects and non-architects. Firstly, the tallest bins of architects are closer to 'Original' (1.00) than the tallest bins of non-architects. It implies that architects tend to be more lenient than non-architects at seeing design variants as original. This observation is corroborated by the higher mean (0.76) and median (0.83) originality scores by architects compared to the mean (0.59) and median (0.62) originality scores by non-architects. In fact, the mean and median originality scores by architects are between the 'Different' and 'Original' categories in the Likert scale, whereas for non-architects they are between the 'Similar' and 'Different' categories.

The second differentiator is that the tallest bins of architects are taller than the tallest bins of non-architects. It implies that architects tend to have a higher consensus than non-architects at reading the visual perception of originality. This observation is corroborated by the lower coefficient of variation (0.22) of the originality scores by architects compared to the coefficient of variation (0.39) of the originality scores by non-architects. In fact, in the case of non-architects, the coefficient of variation is higher than the step value (0.33) of the Likert categories. Additionally, the numerical analysis of the originality scores (see Table 3) reveals that an architect is 17.14 times likely to

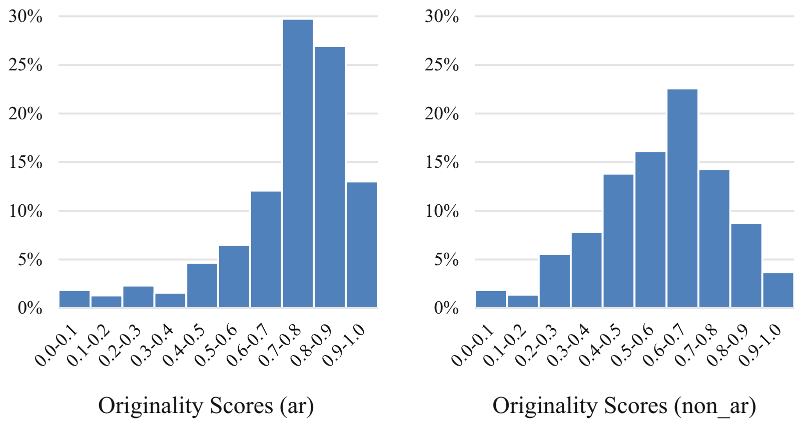


Fig. 10. Percentage distribution of predicted originality scores by architects and non-architects

see a design variant as 'Original' instead of 'Plagiarised', whereas, for a non-architect, the likelihood drops down to 5.26 times.

Table 3. Numerical summary of the predicted originality scores.

Description	Originality score (ar)	Originality score (non_ar)
Mean	0.76	0.59
Median	0.83	0.62
Standard deviation	0.17	0.23
Coefficient of variation	0.22	0.39
Original/Plagiarised ratio	17.14	5.26

Subsequently, the comparative relation between the originality scores by architects and non-architects was ascertained (see Table 4). The average originality score by architects (0.76) is 0.16 higher than the average originality score by non-architects (0.59). In other words, the average originality score by architects is 27.74% higher than the average originality score by non-architects. The mean difference of corresponding originality scores by architects and non-architects is 0.18. In other words, on an average, each originality score by architects is 38.94% higher than the corresponding originality score by non-architects. In as many as 92.01% of the 15,000 design variants, architects' originality score is higher than non-architects'. When the data distribution of the originality scores by architects and non-architects is analysed with respect to the Likert scale categories, the finer differences become clear. Compared to an architect, a non-architect is 1.71 times likelier to see a design variant as 'Plagiarised', and 3.14 times likelier to see a design variant as 'Similar' or 'Different'. On the other end of the spectrum,

Table 4. Numerical summary of the comparative relation of predicted originality scores.

Description	Value
Mean originality score (ar-non_ar)	0.16
Mean originality score percentage ((ar-non_ar)/non_ar)	27.74%
Mean difference (ar-non_ar)	0.18
Mean difference Percentage ((ar-non_ar)/non_ar)	38.94%
Originality score (ar > non_ar)	92.01%
Plagiarised rating occurrence (non_ar/ar)	1.71
Similar & Different ratings occurrence (non_ar/ar)	3.14
Original rating occurrence (ar/non_ar)	1.93

non-architects display the same propensity for being less lenient at labelling a design variant as original. Compared to a non-architect, an architect is 1.93 times likelier to see a design variant as 'Original'.

All of these observations reiterate that architects tend to be more lenient than non-architects at seeing design variants as original. It may be argued that architects are trained to observe the nuances of visual difference between artefacts. Consequently, what may seem like same artefacts to non-architects will look more varied (~ comparatively original) to architects. The other takeaway is that architects have a higher consensus than non-architects at evaluating the originality of design variants. This phenomenon may be attributed to similar rigour of academics and training of architects compared to a more diverse academic and professional background of non-architects. It is to be noted that the reasons speculated behind the varied observations are rather anecdotal in nature. Anecdotal correlations are often not causal. A psychological and/or neuro-response study is needed to explain the subliminal reasons for the observed variance.

The outcome of this study has implications on the decision-making of cityscape preservation and on the architect-client interaction. The decision to preserve or facelift properties and precincts in cities are usually taken by architects, planners, art historians and politicians. The quantitative difference in visual perception of design between architects and non-architects indicates that without direct representation of residents, such a decision making body may miss out on properties and/or precincts that may have sentimental value for the residents. Secondly, the methodology used in this paper can be used to better understand the aesthetic sensibilities of a client. The client may be asked to rate few design options generated by the parametric definition of a design concept. The options may be rated for a variety of keyword-driven subjective opinions, e.g., originality, beauty, appropriateness, etc. Subsequent to training a neural network with the collected data, design may be optimised in tune with the client's subjective opinion(s) along with the regular objective design goals of energy consumption reduction and daylighting.

5 Conclusion

Subjective evaluation of the visual perception of originality of the rotating tower typology by architects and non-architects is predicted by training two deep neural networks with crowd-sourced data of 250 data samples. Use of neural network allows the appropriation of the entire solution space by using limited number of training data samples. Predictions of 15,000 design variants are tabulated to quantify the differences of originality scores between architects and non-architects. It is concluded that the average originality score by architects is 27.74% higher than the average originality score by non-architects. Compared to a non-architect, an architect is 1.93 times likelier to see a design variant as original. In fact, in 92.01% of the cases, architects' originality score is higher than non-architects'. Within themselves, architects tend to have a higher consensus than non-architects at reading the visual perception of originality. Analysis of the correlations of the independent variables revealed that both architects and non-architects tend to subliminally concentrate more on visual features that horizontally control the overall silhouette of towers (such as the shape of floor plan). Additionally, architects tend to be more visually sensitive towards rotation of floor plates, whereas non-architects tend to see rotated towers as a visually homogeneous group without much regard to the amount of rotation. Interestingly, both architects and non-architects tend to ignore local articulation of surfaces when comparing the overall shapes of design variants.

The methodology of training a neural network on crowd-sourced data marks a departure from the top down evaluative guidelines published by experts to a more inclusive bottom up evaluation by end users. The methodology can be used to quantify subjective evaluation of any kind. Beauty or safety perception of urban streetscapes can be predicted as a part of urban design aid by training a neural network with crowd-sourced ratings of photographs of urban streetscapes. The independent variables for such an exercise can be calculated by applying image segmentation [32] on the photographs to extract the areas and mutual positions of roads, signage, greenery, sky, vehicles, etc. Subsequently, the trained network can be used to calculate the fitness function of an evolutionary algorithm to optimise design proposals. The socio-cultural bias embedded in crowd-sourced evaluation can be utilised to analyse and predict design preferences specific to groups of people. For example, in the case of predicting beauty or safety perception of urban streetscapes, evaluation data may be categorised by the cities of residence of the participants. Consequently, the same design proposal will have different predicted scores not only depending on its location, but also on the basis of how it is perceived by different age groups, race, gender, etc.

The future scope of this research is twofold. Firstly, the subjective evaluations by architects and non-architects are to be repeated with the extruded glass box design variant as the reference design. This exercise will establish the effect (if any) of changing the reference design on the visual perception of originality. Secondly, the methodology discussed in this paper is to be applied to different building typologies. A summation of results of multiple typologies will comprehensively quantify the differences of visual perception of originality of design between architects and non-architects in global terms.

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