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Consideration of people's design preferences for the development of adaptive user interfaces

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Abstract: Adaptive user interfaces enable the display of user-specific, relevant information in complex interactive systems. The user experience on platforms can be improved by taking the user's needs (goals, system experience, etc.) and design preferences (in terms of design shapes) into account. In a Germany-wide online survey, $n = 1{,}044$ young people (pupils and university students) aged between 14 and 35 were asked about their design shape preferences. The results show that, overall, the shape of the *circle* appears to be the most attractive for young people (14–35 years) and that gender and age have the greatest influence on design shape preferences. While men and generally older people (19–35 years, university students) prefer basic shapes to more complex shapes, women and generally younger people (14–19 years, pupils) find complex shapes more attractive than basic ones. The identification of preferences with regard to design shapes can provide developers of interactive systems with information for the design of (adaptive) user interfaces.

Keywords: adaptive user interfaces; interactive systems; design; shapes

1 Introduction

Adaptive user interfaces (AUIs) are user interfaces that adapt to the individual needs of the user [1,2] often based on predefined rules and user input.[3] User interfaces that use intelligent technologies are referred to as IUIs.[4] Over the years, *intelligent* has been characterized in many different ways.[5] One characteristic of humans has been transferred to the field of computer science, with aspects such as adaptation, automation and interaction most frequently used by researchers to describe something as intelligent.[5] Basically, an implicit understanding of "intelligent" seems to be assumed at present.[5] IUIs adapt dynamically to the context of use and the environment[2] as well as to the abilities[6] and impairments[7] of the user, for example by using artificial intelligence (AI) or machine learning (ML).[4] They offer deeper adaptivity and context sensitivity and support multiple modalities (e.g. speech, text, gestures, etc.), can also process incomplete input and learn from interactions.[3] It can therefore be summarized that not all AUIs are intelligent.[8] We use the generic term IUIs in the following, as this also implies AUIs. IUIs can adapt to user preferences and needs (e.g. streaming services, accessibility settings and voice-controlled assistants) social media, web and app usage behavior, habits, experiences, but also to network conditions, context conditions (outdoor, indoor (lighting conditions)) and different devices (responsive design). There are also adaptable UIs, where the user interfaces are adapted by the users and not by the system.[1,2] The adaptivity of user interfaces can improve usability, user experience, learnability and accessibility[4,9,10] and overcome the cognitive burden of complex UIs through customized support,[11] thus potentially increase user motivation. By integrating additional data sources into IT environments, users can thus be provided with the best possible user experience. By capturing biometric data, such as facial expressions, and by measuring biosignals, i.e. biological activities (e.g. ECG, EEG, EMG), further exciting insights could be gained for IUIs.

For the design of IUIs, shapes that are appealing for different user groups and fulfill both functional and aesthetic purposes are crucial. Shape preferences of potential users may vary depending on cultural background[12] or gender.[13,14] By shapes we mean two-dimensional objects (height and width) and initially not forms with three dimensions (height, width and depth).[15] Shapes can also evoke (desired) emotional responses from users, influence aesthetic perception, improve the user experience and increase accessibility.

Against the background of the development of a career guidance platform for young people especially from rural regions (who are faced with a migration decision in addition to a career choice decision) as part of a research project, we are interested in how digital platforms can be optimally designed for young people. As we are also heavily

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involved in the development of learning platforms for students, in this article we investigate whether age, gender, region (predominantly rural/urban) or cultural background of pupils and university students have a predictive influence on design preferences regarding design shapes. First, an adaptive user interface design model is established and reference is made to customizable components of a user interface. Visual design in particular is the focus of this paper and the following research question (RQ) is investigated: *What shapes are preferred by young people (pupils and university students, aged 14–35) and what influences their design preferences?*

2 Related work

According to Norcio & Stanley *"The idea of an adaptive interface is straightforward. Simply, it means that the interface should adapt to the user; rather than the user adapting to the system"* [ref. [16], p. 399]. Adaptive graphical user interfaces, in particular menu-driven interfaces, were investigated as early as 1989 in a study by Mitchell and Shneiderman.[17] The menu items were rearranged depending on the frequency of use. However, the reorganization of the menu items did not lead to an increase in performance, but rather to a disorientation of the participants.[18] Nowadays, large companies are working on the implementation of adaptive graphical user interfaces to improve the workflow. Siemens has already implemented AUIs that use artificial intelligence in its CAD software.[19] When using the software, the user interface is personalized based on user patterns and behaviour. The software can predict commands and optimize workflows. Klock et al.[20] developed a conceptual model for the adaptation of gamification elements in educational environments. Based on related work, the characteristics of students were considered when implementing adaptive gamification elements in the open source hypermedia system for distance learning called AdaptWeb®.[21] AUIs are often used in medicine, where the personalized presentation of information can be beneficial for doctors, nurses and patients.[22–24] Furthermore, there are digital platforms (e.g. for career guidance) that provide different themes for users to choose from (candy, cool, normal).[25]

In the field of online teaching, learning paths, material and feedback are adapted on the basis of learning style,[26,27] motivation,[26] performance and support needs. Using integrated learner models in learning management systems (LMS), students can be offered individualized digital support based on user characteristics.[28] A modular, distributed system architecture can enable the adaptation of personalized learning environments so that students can be confronted with individual learning environments.[28] Personality types could be recorded and design preferences for the presentation of adaptive graphical user interfaces could be derived. Multimodal learning is possible, for example, on the basis of format preferences (such as videos, interactive exercises, etc.).[29,30] According to Miraz et al., user interfaces require a high degree of customization to make them usable for people with different cultural backgrounds.[31]

There are various shapes for the design of user interfaces – for the interaction between users and systems. In addition to functional elements such as buttons, menus and icons, shapes also play a role in the overall design. Shapes can have different effects. Stiny extended the mathematics for shapes, which initially consisted of lines, to one that also included points, lines, planes, or solids. These new mathematical structures were then used to perform complex shape calculations with shape grammars.[32] These *"Shape grammars promote an improvisational, perceptual, and action-oriented approach to designing"* [ref. [33], p. 973]. Basic geometric shapes – especially known from historical architecture – include *circles*, *triangles* and *squares*.[34–36] According to Gestalt principles, these basic shapes are easy to recognize and describe.[36,37] There are also more complex shapes,[38] such as *helices*, *organic* and *abstract shapes*, which can arise from the combination and transformation of simple basic shapes or emerge in their decomposition from simple geometric ones.[39]

In this paper, we examine the preference for certain basic and complex shapes. Shapes can, for example, create visual hierarchies and structures on a platform and create a dynamic or less dynamic appearance. The same applies to symmetry. Shapes can be directional cues with regard to navigation or illustrate interactive elements and give a platform an innovative, modern appearance. Finally, studies show that user satisfaction and efficiency appear to be closely linked to the perception of the design.[40] New technologies also seem to be better accepted and more likely to be used if their design meets both aesthetic and functional expectations.[41] Users who feel comfortable with the design of a user interface tend to recommend the application to others and also use it in the long term.[42,43] Therefore, studying shape preferences can significantly contribute to increasing user satisfaction and promoting efficiency.[44] Furthermore, preferred shapes can also give us an indication of the design and choice of typography, which can be used to increase the motivation to use. The motivation to use the system can be influenced by internal factors (e.g. satisfaction), external factors (e.g. rewards)[45] and the usability and usefulness of the system.[46,47] Basic shapes such as the *triangle*, the *square* and the *circle* are often used as backgrounds for app icons on smartphones[48,49] and are also used to separate content on websites or are also frequently used as background patterns. *Squares* generally seem to stand for discipline, strength, reliability and safety and *triangles* for excitement, risk, sharpness and balance.[50] *Circles* seem to stand for lightness, happiness, movement and infinity and *helices* for growth and creativity.[50] *Organic shapes* and *helices* as well as *abstract*, modern shapes are also frequently seen on user interfaces today. *Organic shapes* seem to symbolize freedom and nature and are becoming increasingly popular, especially with the growing environmental awareness.[51,52] *Abstract shapes* seem to stand for uniqueness[50,53] and are currently trending especially in web design.[54] We will therefore take a closer look at these six shapes and their perception in this article.

According to studies, the Big Five personality factors are only weak predictors of artistic preferences in general.[55] However, the perception of shapes could differ based on region.[56] There are studies that suggest that older infants (20 weeks old) prefer patterns with more contours than younger infants (13 weeks old)[57] and also studies in which *squares* and *circles* were strongly associated with gender concepts (masculinity/femininity).[58] In general, curved lines seem to be perceived as more attractive than angular or straight lines.[59,60] First, we look at the essential components of an IUI in the context of learning and skills development and then examine the effect of shapes.

3 Intelligent User Interface Design Model

For the development of adaptive digital platforms in the context of learning and skills development a framework for personalized virtual learning environments (AdaptiveVLEs) for adapting learning paths[61] and an ontology-based learner model based on learning style and motivation and provides suitable materials,[26] among others, exist. A learner model (LM) usually has three main objectives; 1) *knowledge assessment* 2) *plan recognition* and 3) *action prediction* and occurs in conjunction with a domain model (DM), which represents the target area or concepts, the interface model (IM), which describes the interface with which users interact and a tutoring model (TM), which makes pedagogical decisions based on the knowledge of the students in a needs-oriented manner.[62] Hussain et al. also describe a context model (CM) to adapt systems to the environment, be it through different environmental variables such as light and noise, e.g. using environmental sensors.[9] According to Norcio & Stanley,[16] an adaptive interface should basically comprise a knowledge base with four domains; 1) *knowledge of the user*, 2) *knowledge of the interaction* (modalities, dialogue management), 3) *knowledge of the task/domain (goals)* and 4) *knowledge of system's characteristics*.[63,64] However, Völkel et al. identified a lack of standards for the interface design for intelligent technology.[5] Furthermore, many models are very abstract, some characterize the integrated models[65] but do not focus on the user interface components, especially the visual design.

A model for the design of adaptive digital platforms in the context of learning and skills development is proposed by the authors (see Figure 1). We call it model and not framework, as it represents system components abstract. The initial aim is not to specify a detailed model-based system – a lot of research regarding e.g. user models[16,66] and conceptual frameworks[65,67] exist – but rather to show developers and designers customization options with regard to the design.

The model can be used as early as the idea generation stage and is structured as follows: Each user has different ***preferences***, ***needs*** and ***habits*** etc. which are summarized under ***"individuality"*** and can be used to model a user model.[1] The user model can include implicit data (user behavior) as well as explicit data (e.g. user settings) and context-sensitive data.[9] We focus on data collection within the system. ***Data capture*** is possible by the system alone (e.g. through pattern recognition, tracking) using e.g. ***artificial intelligence***[3] or through a cooperative process (e.g. through user input via ***system dialog***)[68] or through capturing ***bahaviorial data*** via ***sensors and input devices*** (e.g. biosignals, eye-tracking). ***User interfaces*** can be adapted in terms of ***components*** like the ***visual design*** (font, shapes, colors, etc.),[9,69] different ***profiles*** can be illustrated, for example by loading different ***stylesheets*** (e.g. using media queries)[70] based on the user's preferences ***(Individuality)*** or accessibility requirements. Other ***user interface components*** that play a role in the development of digital platforms in the context of learning and skills development are, in addition to the ***visual design***, often ***gamification*** elements (e.g. badges and progress bars),[71] ***navigation*** through the learning content, the available ***functions, tasks*** and also ***data and information presentation*** (e.g. the reflection of e.g. learning behavior).[72,73] ***Multimodality*** was generally considered as a ***UI component*** and refers to different forms of communication and presentation of the ***learning content***.[74] In addition, when designing digital platforms in the context of knowledge acquisition, ***intervention repertoires*** (possibly also with different escalation levels or support requirements) can be provided

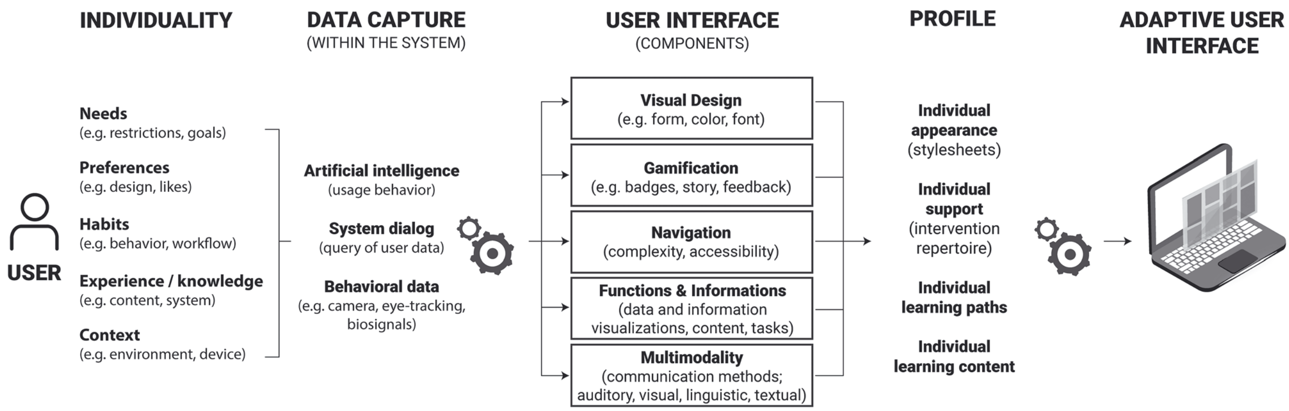

Figure 1: Intelligent user interface design model.

alongside ***individual learning paths***[75] and ***learning materials*** (see Figure 1, profile illustration). In our research project, the idea is to offer users of the career guidance platform JOLanDA,[71] among others, different levels of support via various scenarios based on a different ***intervention repertoire***. The system should adapt as automatically as possible to the needs of the users.[76]

In this paper, we focus on adaptivity in terms of ***visual design***, in particular on the study of users' shape preferences.

4 Methods

Within an online study via a panel (Bilendi/Respondi), $n = 1044$ young people ($n = 585$ pupils ($M = 16.2$ years, SD = 1.477 and $n = 459$ university students ($M = 23.7$ years, SD = 4.522) between the ages of 14 and 35 in Germany were asked about design preferences. We chose the age limit in order to collect data from young schoolchildren (pupils) as well as from university students (including people who have completed a longer educational path up to 35). So only young people between the ages of 14 and 35 were included in the data set; this was ensured by a filter question at the beginning of the questionnaire. The raw data set initially amounted to $n = 1302$, whereby data records with a very short processing time (Dwell time < 360 s or RSI value > 2, because values >2 should be viewed critically[77]), incomplete data (abort during the answering process) and duplicate tickets were sorted out. In addition to design style preferences (flat-, isometric-design etc.) – which is not covered in this article – preferences for shapes were examined by means of the question: *Which shapes do you generally like?* There were six shapes in line to choose from that are frequently used in the design of user interfaces, three basic shapes such as: *square, triangle, circle* and three complex shapes, such as *helix, organic* and *abstract shapes*[78] (see Figure 2). The test subjects could select the shapes (binary) that they found attractive. Several answers could be selected. A developed career guidance platform was then presented via video and specific questions were asked about some design features. However, this is also not part of this report. We also asked the participants whether they had previously lived mainly in rural or urban regions. The data was analyzed and evaluated using SPSS 29.

5 Results

Of the $n = 1044$ test subjects, $n = 374$ lived rather in rural regions (of which $n = 236$ were female, $n = 138$ were male, $n = 149$ were university students and $n = 225$ were pupils) and $n = 510$ tended to live in urban regions (of which $n = 228$ were female, $n = 282$ were male, $n = 250$ were university students and $n = 260$ were pupils). Of $n = 1044$ probands, $n = 986$ were born in Germany and $n = 60$ in another country (from 38 different countries).

Overall, the *circle* appears to be one of the most popular shapes (61.6 %), followed by the *square* (39.2 %), the *helix* (38.1 %), *organic* (36.3 %) and *abstract shapes* (34.4 %). The *triangle* appears to be the least attractive, with just over a quarter of respondents (28.8 %) finding the triangular shape attractive.

First, individual correlations and mutual influences of the variables were examined.

In comparison, the basic shapes *(square, triangle* and *circle)* seem to be preferred by university students (19–35 years) compared to pupils (14–19 years) and the more complex shapes (such as the *helix, organic* and *abstract shapes*) by pupils compared to university students (see Figure 3A).

To test the independence of the categorical variables, a Chi^2 test was evaluated. The expected cell frequencies were

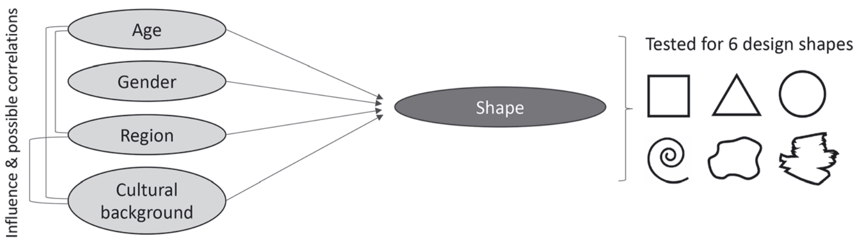

Figure 2: Investigation of the predictive performance of different variables on the design shapes.

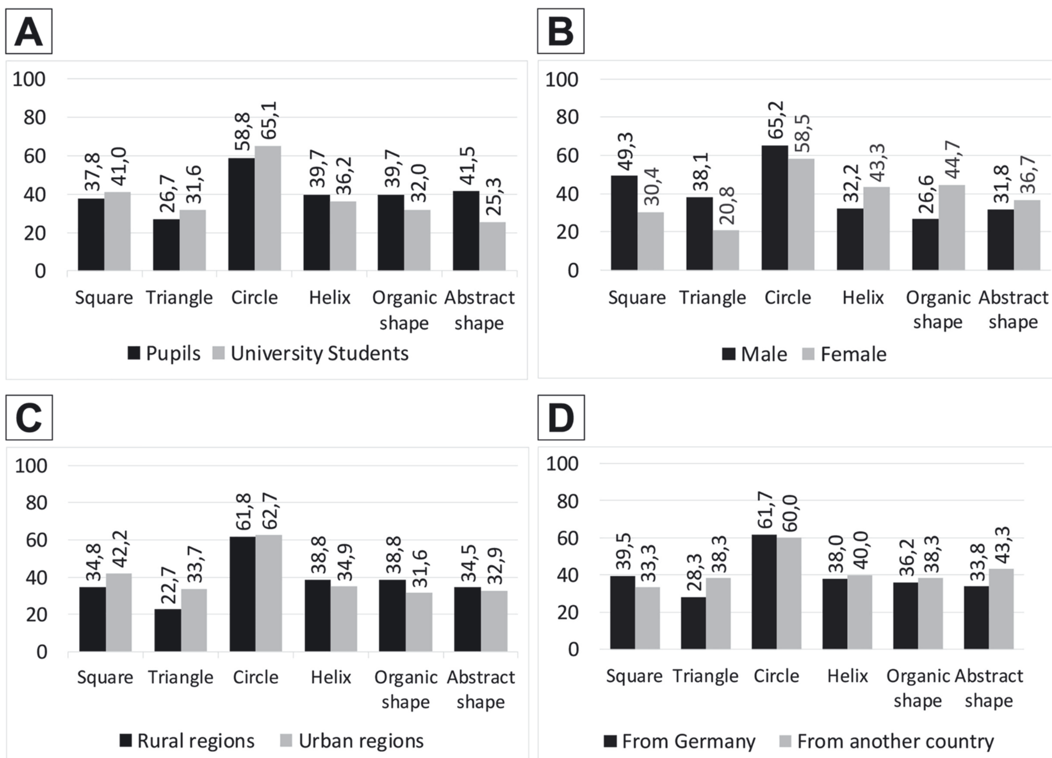

Figure 3: Results of the individual analysis (preliminary investigation). Percentage figures.

not below 5 (important for the accuracy of the test statistics and the stability of the results), so Fisher's exact test – which is more suitable for small samples – was not evaluated.[79,80] The test shows a highly significant correlation between the attractiveness of *circles, organic* and *abstract shapes* and educational status (pupil/university student). This means that educational status and the preference for design shapes appear to be related for the *circle,* for *organic shapes* and for *abstract shapes* (see Table 1). However, the correlation is low (Cramer-V) for *circles* and *organic shapes* and also not particularly strong for *abstract shapes*.

Furthermore, more precise univariate analyses of variance (linear models) of the metric variable *age* and the individual design shapes show significant correlations for the *triangle* ($F(1, 1042) = 10.747$, $p = 0.001$, $n = 1044$), *circle* ($F(1, 1042) = 4.046$, $p = 0.045$, $n = 1044$), *organic* ($F(1, 1042) = 7.173$, $p = 0.008$, $n = 1044$) and *abstract shapes* ($F(1, 1042) = 22.637$, $p < 0.001$, $n = 1044$). No significant correlations were observed for the *square* and the *helix*.

Table 1: Relation between nominal variables education (pupils/students) and shape (not selected/selected).

	Chi^2	df	*p*	Cramer-V
Square	1.092	1	0.296	0.032
Triangle	3.039	1	0.081	0.054
Circle	4.368	1	0.037[a]	0.065
Helix	1.330	1	0.249	0.036
Organic shape	6.479	1	0.011[a]	0.079
Abstract shape	30.161	1	<0.001[c]	0.170

[a]<0.05, [b]<0.01, [c]<0.001.

Thus, age seems to play a role in predicting the preference for design shapes, especially for *abstract* and *organic shapes* as well as basic shapes such as the *triangle* and the *circle*. Age does not play quite as big a role in predicting the preference for *squares* and *helices*.

It is also clear that men find basic shapes *(square, triangle, circle)* more attractive compared to women. Compared to men, women find more complex shapes *(helix, organic and abstract shapes)* more attractive (see Figure 3B). The Chi^2 test shows that gender and preference for design shapes appear to be related for the *square*, for the *triangle*, for the *helix* and *organic shapes* (see Table 2). According to Cohen,[81] however, these are weak to medium correlations.

The respondents could indicate where they had lived most of their lives, whether in urban or rural areas. There was also the alternative category "neither" ($n = 160$), which was filtered out to sharpen further consideration. It can be seen that the preferred design shapes seem to be related to the region in which the respondents have lived most of their lives (urban/rural) (see Figure 3C). It can be seen that the basic shapes *(square, triangle, circle)* are preferred by people from urban regions compared to people from rural regions and that the complex shapes *(helix, organic and abstract shapes)* by people from rural regions compared to people from urban regions. The variable correlation between the nominal transformed dichotomous variable region (rural/urban) and the shape (not selected/selected) was then examined more closely using cross-tabulations. The Chi^2 test shows a highly significant correlation between the attractiveness of *triangles* and the region as well as significant correlations between the region and the attractiveness of *squares* and *organic shapes* (see Table 3). Even if these are weak correlations.

In terms of origin, it can be seen that people born in Germany prefer basic shapes like *squares* and *circles* compared to people from other countries. *Triangles* and complex shapes (such as *helix*, *organic* and *abstract shapes*) are more preferred by people from other countries than by Germans. However, the Chi^2 test shows no significant correlations between the attractiveness of shapes and origin (see Table 4).

The interim results indicate that the basic shapes are preferred more by older people (19–35 years, university students), people from urban regions and men, while pupils (14–19 years), people from rural regions and women tend to prefer complex shapes in comparison (see Figure 4).

Age, gender and region therefore have a potential influence on the preference for design shapes, although the effects are small to medium in some cases.

Of those who stated that they had previously lived in rural areas, 63.1 % were female and 36.9 % male. Of those who stated that they had previously lived in urban areas, 44.7 % were female and 55.3 % male.

Therefore, logistic regressions were calculated in SPSS 29.0 to exclude false correlations and to analyze the relationship between the dichotomous (binary) dependent variables (design shapes) and several independent variables (dummy variables and the metric variable *age*). The logistic regression enables the simultaneous analysis of different influencing factors (e.g. age, gender, origin) on design preferences and thus provides valuable insights into the design of digital platforms. First, for each model *(square, triangle, circle, helix, organic* and *abstract shapes)*, the prerequisites

Table 2: Relation between nominal dichotomy variables gender (female/male) and shape (not selected/selected).

	Chi^2	df	*p*	Cramer-V
Square	38.793	1	<0.001[c]	0.193
Triangle	38.287	1	<0.001[c]	0.192
Circle	4.865	1	0.027[a]	0.068
Helix	13.629	1	<0.001[c]	0.114
Organic shape	36.893	1	<0.001[c]	0.188
Abstract shape	2.786	1	0.095	0.052

[a]<0.05, [b]<0.01, [c]<0.001.

Table 3: Relation between nominal dichotomy variables region (urban/rural) and shape (not selected/selected).

	Chi^2	df	*p*	Cramer-V
Square	4.962	1	0.026[a]	0.075
Triangle	12.657	1	<0.001[c]	0.120
Circle	0.088	1	0.766	0.010
Helix	1.392	1	0.238	0.040
Organic shape	4.944	1	0.026[a]	0.075
Abstract shape	0.233	1	0.630	0.016

[a]<0.05, [b]<0.01, [c]<0.001.

Table 4: Relation between nominal dichotomy variables origin (Germany/other countries) and shape (not selected/selected).

	Chi^2	df	*p*	Cramer-V
Square	0.912	1	0.340	0.030
Triangle	2.801	1	0.094	0.052
Circle	0.068	1	0.794	0.008
Helix	0.095	1	0.758	0.010
Organic shape	0.114	1	0.736	0.010
Abstract shape	2.258	1	0.133	0.047

[a]<0.05, [b]<0.01, [c]<0.001.

	1	2	3	4	5	6
Male	Circle	Square	Triangle	Helix	Abstract	Organic
Students	Circle	Square	Helix	Organic	Triangle	Abstract
Urban regions	Circle	Square	Helix	Triangle	Abstract	Organic
Female	Circle	Organic	Helix	Abstract	Square	Triangle
Pupils	Circle	Abstract	Helix Organic		Square	Triangle
Rural regions	Circle	Helix	Organic	Square	Abstract	Triangle

Figure 4: Preferred design shapes in order of 1–6 (percentage descending) by gender, educational status (also reference to the age) and region. Basic shapes in dark grey and complex shapes in light grey.

for conducting a logistic regression for each of the six models were checked so that; 1) no outliers are present, 2) loglinearity is present and 3) no multicollinearity is present.

For more robust regressions, bootstrapping[82] was used if the conditions were not met. This involves sampling to ensure that the results are also reproducible with other data.

5.1 What influences the preference for basic shapes?

The loglinearity requirement was not met for all regression models, so bootstrapping (2500 samples, BCa method) was used for validation. The 1st regression model *(square)* is significantly better than the 0 model (χ^2 (4, $n = 884$) = 34.738, $p < 0.001$) and has a goodness of $R^2_{\text{Nagelkerke}} = 0.052$ auf (see Table 5).

Overall, 60.4 % can be correctly predicted with the model with a sensitivity of 26.4 % and a specificity of 82.2 %. The gender female differs significantly from the reference category male ($p < 0.001$) and has a regression coefficient B of −0.745 (see Appendix, Table 6), i.e. the preference for *squares* decreases if the person is female. The probability is therefore (OR = 0.475–1 = −0.525, i.e. 52.5 %, see Appendix, Table 5) 52.5 % lower that female persons (reference category male) have a preference for *squares*.

According to the model, the region in which the test subjects have lived most of the time or the origin (country) have no significant influence on the preference for *squares*. The probability of having a preference for *squares* increases by 21.4 % (OR = 1.214–1 = 0.214, i.e. 21.4 %) if the subjects come from urban regions.

The 2nd regression model *(triangle)* is also significantly better than the 0 model (χ^2 (4, $n = 884$) = 46.187, $p < 0.001$) and has a goodness of $R^2_{\text{Nagelkerke}} = 0.073$. The overall percentage of correct classification was 70.7 % with a sensitivity of 4.3 % and a specificity of 97.9 %. The gender female differs significantly from the reference category male ($p < 0.001$) and has a rerating coefficient B of −0.758, i.e. the preference for *triangles* decreases if the subjects are female. Furthermore, age ($p = 0.005$) and region ($p = 0.027$) are significant. This means that the preference for *triangles* appears to increase with increasing age ($B = 0.042$). The same applies if people have previously lived predominantly in urban regions ($B = 0.364$). The relative probability of a preference for *triangles* is 43.8 % higher (OR = 1.438–1 = 0.438, i.e. 43.8 %) for people from urban regions. Country of origin had no significant influence on the predictive performance of the model.

The omnibus test for the *circle* model is not significant ($p = 0.127$). Overall, 62.3 % could be predicted correctly with a sensitivity of 100 % and a specificity of 0 %. Neither gender ($p = 0.062$), region ($p = 0.855$), origin ($p = 0.660$) nor age ($p = 0.060$) differed significantly in the preference for *circles*. However, women ($B = -0.260$) appear to be less likely to choose *circles* than men (result not significant). All independent variables have no significant influence on the predictive performance of the model.

Table 5: Summarized results of the logistic regression.

Model summaries	Omnibus-test model (Chi^2, df, p)	Prediction (total % of correctly assigned)	Variance clarification (Nagelkerke R^2, 0–1)
Square	34.738, 4, <0.001	60.4 % (Specificity: 82.2 %, Sensitivity: 26.4 %)	0.052
Triangle	46.187, 4, <0.001	70.7 % (Specificity: 97.9 %, Sensitivity: 4.3 %)	0.073
Circle	7.179, 4, <0.127	62.3 % (Specificity: 0.0 %, Sensitivity: 100 %)	0.011
Helix	12.914, 4, 0.012	63.5 % (Specificity: 100 %, Sensitivity: 0 %)	0.020
Organic shape	42.172, 4, <0.001	65.4 % (Specificity: 99.7 %, Sensitivity: 0.7 %)	0.064
Abstract shape	28.365, 4, <0.001	66.5 % (Specificity: 99.8 %, Sensitivity: 0.7 %)	0.044

5.2 What influences the preference for complex shapes?

The 4th regression model *(helix)* is better than the 0 model in terms of the overall percentage (χ^2 (4, $n = 884$) $= 12.914$, $p < 0.012$) and has a quality of $R^2{}_{\text{Nagelkerke}} = 0.020$. The overall percentage of correct classification is 63.5 % with a sensitivity of 0 % and a specificity of 100 %. Only gender has a significant ($p = 0.002$) influence. The preference for *helices* increases if the subjects are female ($B = 0.450$). All other independent variables have no significant influence on the predictive performance of this model.

Overall, it was observed that the 5th model *(organic shapes)* is significantly better than the 0 model χ^2 (4, $n = 884$) $= 42.172$, $p < 0.001$ with a goodness of $R^2{}_{\text{Nagelkerke}} = 0.064$. The overall percentage of correct classification is 65.4 % with a sensitivity of 0.7 % and a specificity of 99.7 %. Of the four variables included in the model, two were significant, age ($p = 0.044$) and gender ($p < 0.001$). While region ($p = 0.299$) and origin ($p = 0.545$) did not appear to have a significant impact on the predictive performance of the model.

Overall, it can be observed that the 6th model *(abstract shapes)* is significantly better than the 0 model (χ^2 (4, $n = 884$) $= 28.365$, $p < 0.001$) and has a goodness of $R^2{}_{\text{Nagelkerke}} = 0.044$. The overall percentage of correct classification is 66.5 % with a sensitivity of 99.8 % and a specificity of 0.7 %. Only age ($p < 0.001$) has a significant influence on the preference for *abstract shapes*. Younger people tend to find more *abstract shapes* more attractive ($B = -0.080$).

5.3 Summarized results

In general, *circles* are among the most favored shapes for young individuals (ages 14–35). Gender significantly affects shape preferences, particularly for *squares, triangles, helices,* and *organic shapes* (see Figure 5). Men tend to favor basic shapes compared to women, while women are inclined towards more complex shapes compared to men. Age is the second most influential factor on design preferences, with younger individuals (pupils) finding complex shapes more appealing than basic ones compared to university students. Notably, preferences for *triangles* are influenced by age, gender, and the region of residence. Country of origin (Germany vs. another country) does not affect shape preference as currently assessed.

The results (Figures 3 and 4) show that the division into the basic *shapes (square, triangle, circle)* and the complex shapes *(helices, organic shapes* and *abstract shapes)* seems to make sense. The direct comparison between pupils versus university students, male versus female, rural regions versus urban regions shows that one group rates the basic shapes better than the other group and vice versa.

To see to what extent the variables are linked, we created a logic tree. This allows us to see in detail how the shape preference changes if the young women come from urban rather than rural regions, for example (see Figure 6).

Again, it is clear that *circles* are preferred by all groups, i.e. both women and men, even when educational status (hint to age) and region are added (see Figure 6, highest percentages outlined). It is also clear that when educational status is added, the results for women do not differ

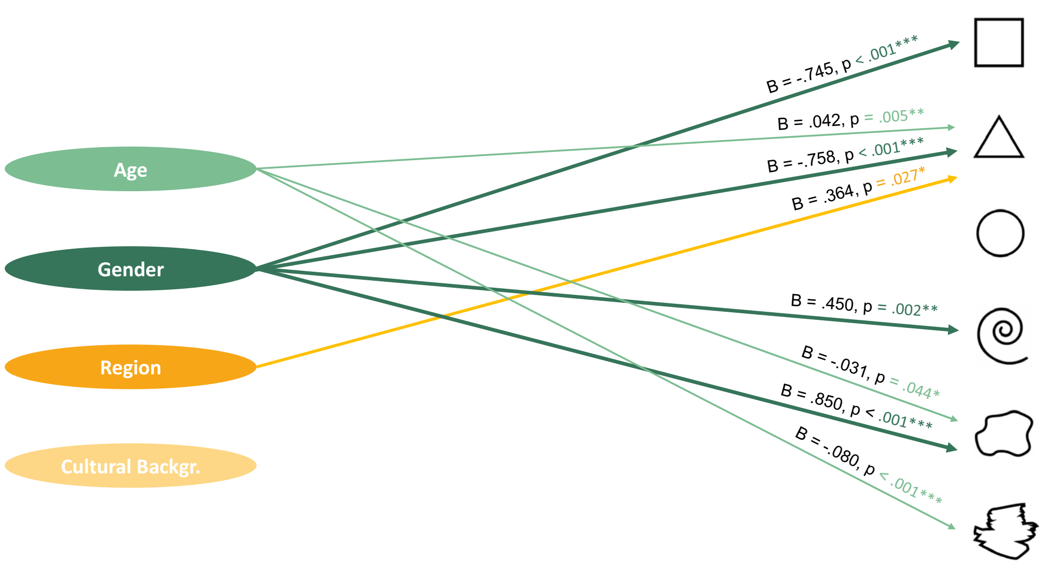

Figure 5: Significant influences on the predictive performance of the models (shapes).

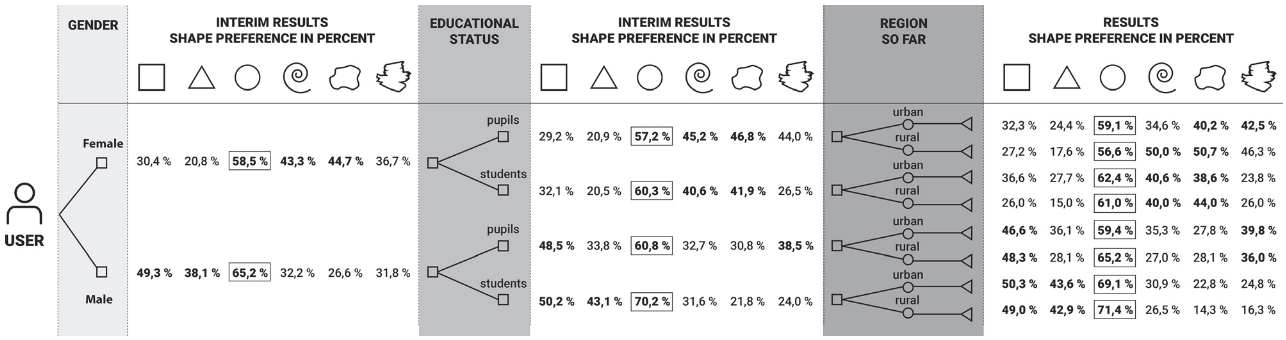

Figure 6: Decision tree with logical and links (the three highest values (form preferences in percent) were marked in bold and the highest of them framed).

significantly from those when educational status (i.e. age) is not taken into account. For men, on the other hand, whether they are younger or older seems to play more of a role. Younger men (14–19 years, pupils) seem to find *abstract* and *organic shapes* better than older men (19–35 years, university students). Older men (43.1 %) seem to find shapes such as *triangles* much better than younger men (33.8 %). Among women, it is noticeable that young women from rural regions (50.0 %) particularly like *helices* more than young women from urban regions (34.6 %). For older women (19–35 years, university students), the region of origin no longer seems to play a significant role. For men, the region of origin does not play a significant role in the order of preferred shape, although the percentage values of the shape preferences differ.

6 Discussion, limitations and conclusion

According to Gullà et al., adaptive user interfaces are one of the most important goals of human computer interaction (HCI) research.[1] Designing for diversity[1] is possible if you know the preferences of the users. In a Germany-wide online survey via a panel (Bilendi/Respondi), young people were asked which shapes they find fundamentally attractive in order to gain insights into preferences and obtain information for the design of user interfaces of digital platforms.

Answering the research question: What shapes are preferred by young people and what influences design preferences? Overall, *circles* seem to be among the most popular shapes among young people, a shape that appears soft and self-contained without edges (see Figure 3A) followed by *squares*. The results are consistent with the findings of other studies in which it was observed that curved lines are perceived as more attractive than angular or straight lines.[60] Furthermore, basic shapes are very familiar to people and these basic shapes can also be found on most user interfaces. In general, young people seem to like *triangles* the least. This is probably because it is often used as a warning symbol to warn of risks and visualizes balance but also illustrates danger.[53]

With regard to the answer to the research question, gender seems to have the greatest influence on the preference for shapes (see Figure 5). Men seem to find basic shapes more attractive compared to women, while women prefer complex shapes more compared to men. This could be due to genetic, hormonal and/or environmental factors[83] as well as the fact that women seem to be better at visual perception and speed of perception and have a more detailed memory than men.[84] After all, studies also show that there are gender-specific differences in color perception that could be evolutionary in origin.[85] It remains to be seen what the perception and design preferences are with regard to more diverse gender identities. It should be mentioned that three people who stated that they were "diverse" took part in the study. Due to the sample size and the associated less meaningful results, these were not focused on in this study (limitation), but further studies in which this group of people is more widely represented should follow in order to be able to make corresponding statements.

Of the variables considered, age appears to have the second greatest influence on design preference. Younger people seem to find the complex shapes more attractive than the basic shapes compared to older people. Perhaps this is due to the fact that people are more playful? This could be tested in further studies using a Playful Scale[86,87] because playful personalities exhibit *"physical, social, and cognitive spontaneity, manifest joy, and sense of humor"*.[88] It may also be due to the fact that adults may have learned to regulate their playfulness.[87] It is interesting to note that the preference for *triangles* is influenced by age, gender and the region in which the test subjects lived. Overall, the *triangle* model works best in terms of variance explanation. The omnibus test was not significant for the *circle*. In addition, the lowest Nagelkerke value can be observed here. This means that the variance explanation for this model is low. The predictors are therefore not particularly suitable for predicting the dependent variable.

The results on cultural background are not broken down further (limitation). Initially, only differences were found between people born in Germany and people born in other countries. A detailed insight into the shape preferences of people from different regions of origin has yet to follow. In addition, factors other than country of birth play a role in determining cultural influence. Other important aspects that can be taken into account were modeled by Reinecke & Bernstein in an ontology for cultural user models.[89] Overall, further studies should follow in order to be able to make statements about cultural influence.

With regard to the limitations of this study, it should also be noted that the respondents were asked to indicate the region in which they had lived most of the time, rural, urban or neither, but were not asked for the exact number of inhabitants, so the assessment is dependent on perception.

The test subjects were asked which shapes they generally find attractive. In summary, we were able to observe two groups when evaluating the data: those who prefer simple shapes and those who find complex shapes more attractive. For a clear design of a user interface, a certain variety of shapes is required, e.g. to display navigation and functional elements. Based on the results, we have developed two exemplary user interfaces (dummies) that can be displayed depending on the group of people (see Figure 7 A, B). *Circles* are integrated in both user interfaces as they are among the most popular shapes overall. This gives designers and developers a clue for the initial development of e.g. mockups, but depending on the application context, it should be checked more closely whether the generally attractive shapes are also attractive in the respective application context or whether other shapes are preferred for UI elements. Furthermore, not all users can be categorized across the board; an individual query or preference analysis could be implemented on digital platforms.

For our project, it is clear that a playful design is suitable for the young target group (predominantly pupils) in the area of career guidance and that the integration of *organic shapes* and *helices* is particularly attractive. We therefore decided to design a platform with a jungle look. Thematically, this fits very well, as the young people can embark on a journey through the (career choice) jungle and explore expedition paths (with corresponding content) by means of a journey of discovery.

In further studies, we observed that the topic of career guidance is also of interest to university students.[47] If you want to ensure optimal accessibility of the platform, an adaptive adjustment of the user interface could be made by integrating more basic forms (attractive for older people (university students)), which would lead to a more orderly design adjustment. For example, the jungle displayed for university students could take on constructivist or even cubist features and consist of more basic geometric shapes.

In further studies, A/B tests could be used to check whether the user groups have a better user experience when a user interface that is attractive to them is displayed.

In addition, further studies on additional predictors could follow in order to improve the variance explanation

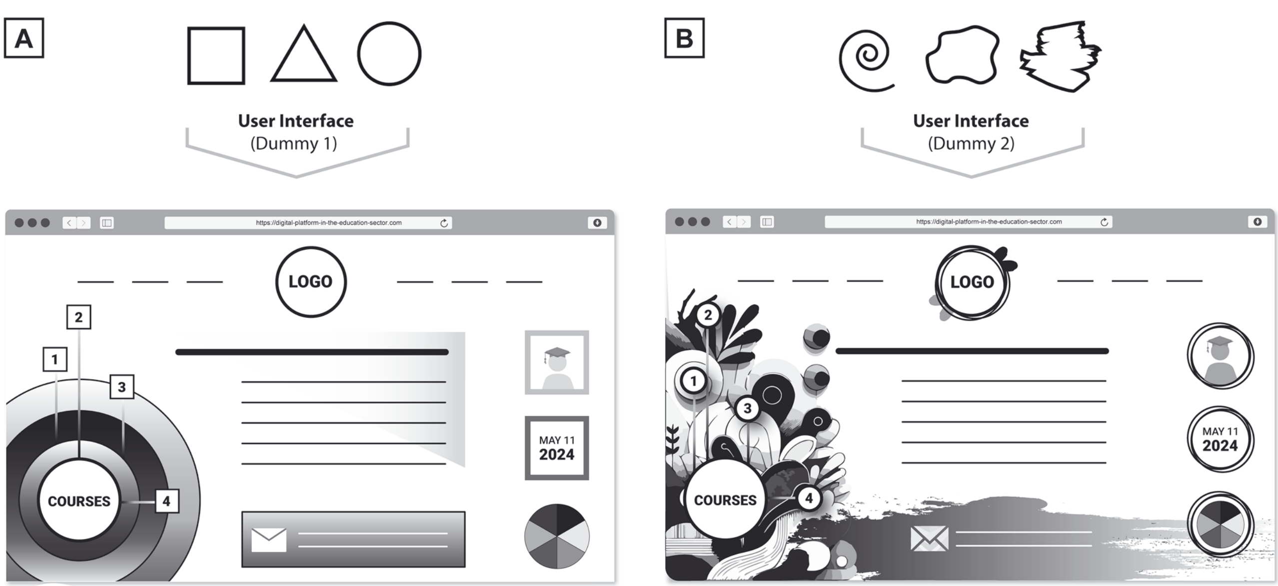

Figure 7: Views of an adaptive user interface of a digital platform in the education sector (dummy).

of the models. Further design elements could also be included. Furthermore, correlations between the preference for shapes and the preference for a particular UI design can provide important insights. The results may be of interest for the development of future adaptive user interfaces and can be incorporated into the development of algorithms, also in combination with other data (e.g. biosignals, biometrics) to increase motivation of users on digital platforms.[31,90,91]

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Author contributions: The authors have accepted responsibility for the entire content of this manuscript and approved its submission.
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Data availability: The raw data can be obtained on request from the corresponding author.

Appendix

See Table 6.

Table 6: Summarized results of the logistic regression models (bootstrapping was performed for all models with $k = 2500$, BCa, bold values are significant).

Model 1 | Square

Parameter	Regression coefficient B [BCa 95 %–KI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	0.011 [−0.018, 0.039]	1.011	0.443
Gender	−0.745 [−1.048, −0.477]	0.475	**<0.001**[c]
Region	0.194 [−0.112, 0.499]	1.214	0.182
Origin	−0.442 [−1.066, 0.112]	0.643	0.150

Model 2 | Triangle

Parameter	Regression coefficient B [95 %–CI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	0.042 [0.011, 0.073]	1.043	**0.005**[b]
Gender	−0.758 [−1.074, −0.457]	0.468	**<0.001**[c]
Region	0.364 [0.037, 0.704]	1.438	**0.027**[a]
Origin	0.225 [−0.439, 0.856]	1.253	0.490

Model 3 | Circle

Parameter	Regression coefficient B [95 %–CI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	0.028 [−0.001, 0.060]	1.029	0.060
Gender	−0.260 [−0.536, 0.004]	0.771	0.062
Region	−0.026 [−0.311, 0.254]	0.975	0.855
Origin	−0.138 [-0.721, 0.521]	0.871	0.660

Model 4 | Helix

Parameter	Regression coefficient B [95 %–CI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	−0.018 [−0.047, 0.011]	0.982	0.239
Gender	0.450 [0.158, 0.732]	1.569	**0.002**[b]
Region	−0.080 [−0.354, 0.197]	0.923	0.567
Origin	0.206 [−0.479, 0.825]	1.229	0.500

Model 5 | Organic form

Parameter	Regression coefficient B [95 %–CI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	−0.031 [−0.063, −0.002]	0.969	**0.044**[a]
Gender	0.850 [0.552, 1.169]	2.339	**<0.001**[c]
Region	−0.155 [−0.449, 0.141]	0.856	0.299
Origin	0.198 [−0.510, 0.828]	1.219	0.545

Model 6 | Abstract form

Parameter	Regression coefficient B [95 %–CI (Bootstrap)]	OR (Odds Ratio)	p (Bootstrap)
Age	−0.080 [−0.115, −0.048]	0.923	**<0.001**[c]
Gender	0.236 [−0.050, 0.540]	1.266	0.106
Region	0.023 [−0.264, 0.327]	1.023	0.875
Origin	0.362 [−0.346, 1.011]	1.436	0.255

[a]<0.05, [b]<0.01, [c]<0.001.

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