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AI-Supported UI Design for Enhanced Development of Neurodiverse-Friendly IT-Systems

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Abstract: With companies like SAP hiring neurodivergent people for specialized technical tasks, the inclusion of neurodivergents gained importance. This inclusion in engineering teams enables companies to leverage the different strengths of both neurodivergents and neurotypicals, enhancing innovation capabilities significantly. This paper presents an AI-based approach for designing neurodiverse-friendly user interfaces (UIs) of IT-systems to facilitate the inclusion of neurodivergents and thus empower team diversity. The methodology is based on data from a survey within the neurodivergent community.

Keywords: Artificial Intelligence (AI), User Interface Design, Neurodiversity, Inclusive Design, Data Mining

1 Introduction

The importance of the user interface (UI) has been massively neglected in recent years. As a result, many IT-systems are rejected by users, even though these systems provide relevant value for their area of responsibility (Pavlov, 2014; Thesmann 2016). UIs are often overloaded with functionality and inconvenient arranged. Thus, users find it difficult to navigate. One reason for this is that developers are concerned that functionality will suffer because of good design (Thesmann, 2016), but this has already been disproved by examples from the physical world. For example, there are now box spring beds that perform many of the functions of a healthcare bed, such as electrically adjustable slats, that make people's lives easier while looking like a normal bed - often with a very modern design. This example illustrates that design and functionality can coexist harmoniously, a principle that extends to IT-systems as well. Since rejection leads to underuse of the system's capabilities (Mejia-Figueroa and Juarez-Ramirez, 2015), it is therefore necessary to focus not only on the functionalities of a system, but also on the design of the UI to ensure a good user experience (UX).

Addressing the UI needs of minorities is a major challenge, especially as the issue of neurodiversity has become increasingly important in recent years. As companies like SAP now prefer to hire autistic people in certain areas (Austin and Pisano, 2017; Brinzea, 2019), the participation of neurodivergent people in neurotypical workplaces should be strengthened. In order to fully utilize the strengths of these groups (Wyrsch et al., 2020), systems must also meet the specific needs of neurodivergent people (Ntalindwa et al., 2021). In fact, dissatisfaction with a UI poses greater challenges for neurodivergent people than for neurotypical people (Ntalindwa et al., 2021), often related to rejection of the IT system. The study referenced in this paper showed that even though the majority of both groups can get used to an unpleasant UI if they have to, only around 11% of neurotypicals would reject the whole system, whereas almost 27% of neurodivergents would do so (see Figure 1). Complicating the situation is the fact that neurodivergents are not only dissatisfied or annoyed, but even develop physical pain as a result (Doyle, 2022; Matejcek, 2017), which negatively affects their (work) performance (Wyrsch et al., 2020).

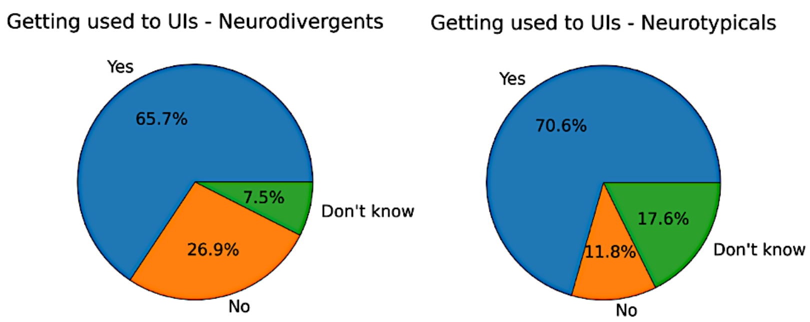

Figure 1. Percentage Distribution of Neurodivergents and Neurotypicals with regard to Adaptation to Unpleasant UIs among the Professional Sectors IT, Production, Mechanical Engineering and Technology

Particularly in times of skilled labor shortages, neurodivergent individuals should be the focus of attention, as under certain conditions and depending on the task, they may be able to replace 2-4 workers (Bruyère and Colella, 2022) due to their cognitive characteristics, such as faster processing of complex problems through, among other things, improved visual perception and understanding of nested relationships. Recent studies show that both, the treatment of comorbidities and the reduction of emotional stress, lead to an improvement of the negative effects of neurodivergence, such as concentration difficulties (Kittel-Schneider et al., 2022). Thus, appropriate UIs could also contribute to the well-being of neurodivergent people by reducing both physical and psychological stress, leading to the exploitation of strengths and enhanced inclusion in the working field of engineering design.

Therefore, the aim of the presented approach is to collect and identify requirements for UIs based on the needs of neurodivergent people as well as the implementation of these needs. However, it should be noted that even within the neurodivergent group there are different requirements and not all of them can be met, so only the overlap within the different neurodivergent groups is considered relevant.

First, the research design is presented, followed by explaining the topic of neurodivergence and its impact on the workplace in general. This is followed by a discussion of related work and some of the results including a short evaluation of the W3C Working Group Note (W3C, 2021). Finally, an initial artificial intelligence (AI) model to support UI design is presented, followed by a discussion of its limitations and future work.

2. Research Design and Survey

2.1 Research Design

At the beginning of this study, individual, formal workshops were held with a total of 16 neurodivergent people. The participants were selected via the associations "Mensa in Deutschland e.V.", "ADHS Deutschland e.V." and "autismus - einfach anders e.V." and are all medically diagnosed as people with autism or ADHD and/or confirmed highly-gifted. During these workshops, all participants were first asked about good and bad characteristics of UIs based on their experiences. Various examples were then shown and used to discuss and identify relevant elements. These included the areas of clear arrangement, structure/scanability, logical structure, contrast, color scheme, font (size), scalability, information content and unambiguousness. The insights gained in the workshops combined with knowledge from literature and practice, including well-known standards such as the W3C standard, served as the basis for the development of the survey. This survey consisted of a total of 133 questions, which were used to collect both personal information and UI-specific data. A pre-test was carried out with neurodivergent and neurotypical people and the questionnaire was revised accordingly before being distributed via "Mensa in Deutschland e.V.", "ADHS Deutschland e.V.", "autismus - einfach anders e.V.", surveycircle and LinkedIn. The questionnaire was also distributed internally at the companies SAP and DATEV. The survey was analyzed using well-known data analytics methods as well as with AI-support (see section 5.1). The insights gained are implemented within a research project and will be discussed with the original workshop participants. The design will be iteratively improved until a satisfactory result is achieved. Finally, a corresponding style guide will be created.

2.2 General Survey Information

The survey started on 06/18/2023 and ended on 12/31/2023 with 222 respondents in total who have completed the entire survey. It consists of 133 questions.

For IT-systems/-tools UI development in engineering, only responses from participants working in IT, mechanical engineering, production as well as technology were considered. This resulted in a total of 84 participants. The total count of participants of each working area as well as the percentage distribution is shown in Figure 2.

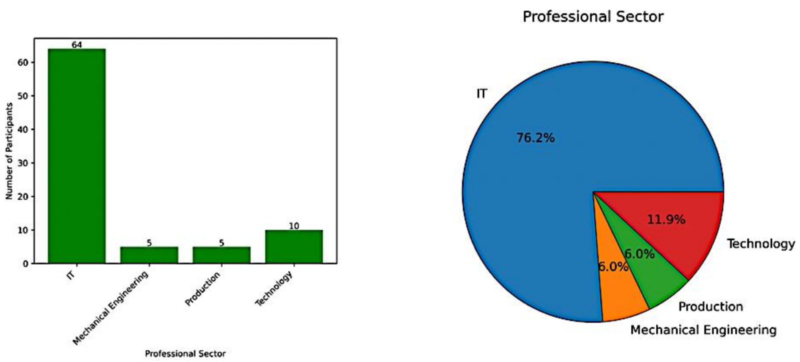

Figure 2. Distribution of Participants among the Professional Sectors IT, Production, Mechanical Engineering and Technology

Further analysis showed that approximately 58% of the participants were male, about 38% female and almost 4% diverse. In addition, about 20% (17 participants) were neurotypical and almost 80% (67 participants) were neurodivergent.

The survey also looked at how much experience the participants had with UI design. The results showed that almost 83% have at least some experience of UI design, of which about 20% have practical experience and around 5% have theoretical experience. Almost 23% have experience of both and about 35% have minimal experience of UI design. Elicitation and assessment of experience of UI design is important to evaluate the participants' validity of answers given in the survey.

3 Neurodivergence and Impacts on the Workplace

3.1 Neurodivergence

As there are regular differences in the development of the brain, the term neurodiversity (not to be confused with neurodivergence) describes an attitude of acceptance of neurological differences between people. This means that autism spectrum disorder (ASD), attention deficit hyperactivity disorder (ADHD) or learning disabilities are considered part of natural variation (Orsini, 2012) and not as a disability. To promote equality and inclusion of neurological minorities, the term neurodiversity emerged in the late 1990s within the neurodiversity movement and is linked to the activist Judy Singer (Houdek, 2022). The terms neurodivergent and neurotypical were introduced to differentiate between neurologically typical and atypical individuals. In this sense, neurodivergent people can be described as those with ASD, ADHD, Dyscalculia, Dyslexia or just specific autistic traits or in general a way of thinking that is considered atypical by society, even including being highly-gifted (Brinzea, 2019; Bruyère and Colella, 2022). As a result, among other things, neurodivergents always assume highly complex structures and behaviors, which leads them to want to know and understand everything in detail (Bruyère and Colella, 2022; Doyle, 2022; Houdek, 2022). An IT-system that is incomprehensible to them - and this includes the UI - leaves them in a state of dissatisfaction.

However, it should be noted that there are different cognitive manifestations within the neurodivergent community and each type of neurodivergence is associated with its own strengths and weaknesses. For example, ADHD is primarily associated with creativity, while dyslexia is associated with a particular type of visual-spatial talent (Houdek, 2022).

3.2 Impacts on the Workplace

A neurodivergent person faces many obstacles in a neurotypical environment. In order to avoid negative reactions from colleagues to the different way of working and thinking, this group of people uses what is known as masking. This involves a compulsive attempt to conform to social conventions, which consumes a great deal of energy (Weber et al., 2022). Furthermore, adaptation is only possible to a limited extent, because not everything can be understood or comprehended.

Figure 3 illustrates the problem in the everyday work of a neurodivergent. The sheep farmer (employer) expects each of his sheep (neurotypical employees) to jump over the fence quickly. The mole (neurodivergent employee) cannot jump over the fence and is worried about the reaction of the farmer, who is already reproaching him that his colleagues can do it better than he can. But the mole can do other things better than jumping - namely digging. The mole immediately finds a solution to get to the other side: he digs a tunnel, which is what he does best.

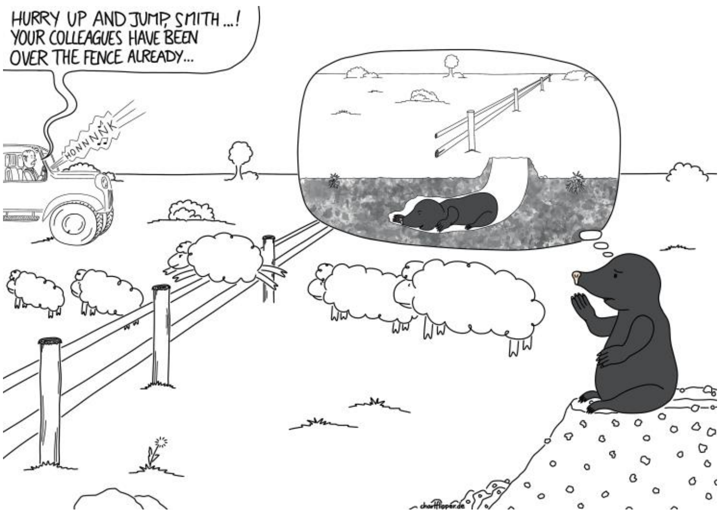

Figure 3. Symbolic Representation of Neurodivergence at the Workplace

The figure shows that neurodivergents have weaknesses, but also strengths. They may not be able to do everything like their colleagues, but they can quickly find an adequate or even better alternative. This also applies to finding solutions to problems. Neurodivergent people consider many alternatives in a very short time and evaluate them accordingly. This makes them a great asset in the workplace. It is therefore important to create satisfactory conditions for them in the workplace - including the UI of the IT-systems they use. Unfortunately, society currently perceives neurodivergent people as disabled and only considers the limitations and not the enrichment of this diversity. However, it is not only society that sees people with autism and ADHD as disabled, but also the World Wide Web Consortium (W3C), as can be seen from the fact that in their 2021 Working Group Note entitled "Making Content Usable for People with Cognitive and Learning Disabilities" they also list personas with ADHD and autism for which style recommendations are given (W3C, 2021). The survey conducted, on the other hand, shows, that neurodivergent people do not see themselves as disabled. Almost 70% state this and less than 23% see themselves as disabled due to their neurodivergence. In addition, only 30% say that they feel (rather) limited in general, while almost 80% even see neurodivergence as an enrichment. The inclusion of this group of people should therefore be promoted (see Figure 4).

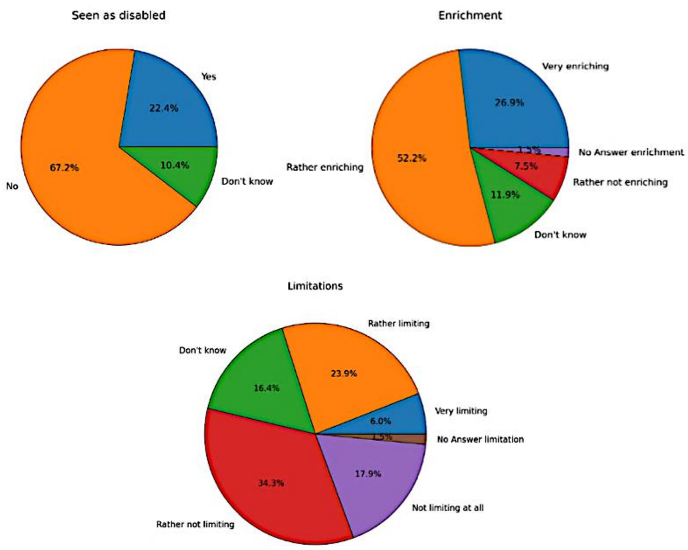

Figure 4. Limitations, Enrichment and Disability Perceived by Neurodivergent People among the Professional Sectors IT, Production, Mechanical Engineering and Technology

4 Related Work

To discern pertinent literature, systematic searches were conducted employing varied combinations of keywords, including neurodiversity, neurodivergence, workplace, autism, ADHD, giftedness, UI design and AI. This search revealed that currently only specific environmental measures are adapted to the needs of neurodivergent people in the workplace (Genaro Motti, 2019; Pavlov, 2014). As these people cannot cope with being disturbed when they are hyper-focused, individual offices, dimmed lighting and noise-cancelling headphones are provided, as well as the opportunity to listen to music while working. Some companies have also introduced a kind of traffic light system (Genaro Motti, 2019) where people can indicate whether they can be disturbed at the moment (green), can be disturbed if necessary (yellow) or cannot be disturbed (red). Since sensory overload is a fundamental problem for neurodivergents, it must be avoided in order to prevent physical and behavioural effects such as meltdowns or shutdowns (Lukava et al., 2022). This is exactly why UIs play a central role. Due to the fact that UIs can very quickly become overloaded or too colorfully designed, a non-neurodivergent-friendly design can become a trigger for this group of people. However, there are currently very few publications that address this topic in the broadest sense (Mejia-Figueroa and Juarez-Ramirez, 2015; Ntalindwa et al., 2021; Pavlov, 2014). Furthermore, these are mainly focused on the design of apps for autistic children (Kamaruzaman et al., 2016; Ntalindwa et al., 2021; Prawira et al., 2017). This is a gap because, as mentioned before, each type of neurodivergence has its own needs and expresses differently, and there are also differences between childhood and adulthood. In addition, these researches have mainly focused on compensating for weaknesses and thus on applications that exist primarily for this target group (Kamaruzaman et al., 2016; Ntalindwa et al., 2021; Prawira et al., 2017). The research presented here aims to design UIs that are suitable for both neurotypical and neurodivergent individuals. There is currently only one publication that at least deals with the design of MBSE tools for neurodivergent system architects (Keil and Bleisinger, 2023). However, it has already been considered important to include neurodivergent people in the development process (Genaro Motti, 2019). Therefore, a broad survey was conducted, including neurodivergent individuals, to address the special requirements of this group for engineering IT-systems. It should be noted, however, that it has already been recognized in the field of virtual reality and augmented reality that other access requirements must be taken into account for neurodivergent people (Lukava et al., 2022; Mai et al., 2023).

Less scientific publications exist on the topic of UI design for neurodivergence. These include, for example, the W3C Working Group Note (W3C, 2021), which cannot be generally applied in its current form and is still incomplete (see section 5.2), and the Neurodiversity Design System by Will Soward (Soward, 2024).

There are also currently only a few publications on AI support in the UI design process, which are also still in the early stages of research (Pandian and Suleri, 2020; Xing et al., 2022).

However, one thing that was very noticeable during the analysis of the state-of-the-art was the fact that there was no inclusion of highly-gifted people anywhere - neither in terms of neurodivergence nor in terms of UI design. This neglect may be due in part to the fact that highly-gifted individuals represent only 2% of the population, and most are either underachievers or pursue careers in research rather than the private sector. However, given the considerable potential within this group, it's imperative to address their needs to bring them into the workforce, especially in times of skills shortages. Therefore, the study presented here attempts to close this gap in the future, as the participants are (also) highly-gifted.

5 AI-Supported Evaluation and Discussion

5.1 AI-Supported Evaluation

AI should assist in analyzing the extensive survey in order to identify participants' preferred elements more quickly. However, the further goal is to reduce the large set of questions to a minimum in order to be able to determine the elements and layout to be included with just a few questions that need to be asked to a user group. This objective results in a multiclass-multioutput classification problem, which makes feature selection in particular more difficult, as known methods cannot simply be used. This section therefore describes an initial approach.

In multiclass-multioutput classification each sample is labelled with a set of non-binary features, where both the number of features and the number of classes per feature are greater than 2. This means that a single estimator performs multiple classification tasks simultaneously. It is an extension of multilabel classification, which deals only with binary features, and is also an extension of multiclass classification, where only a single feature is considered.

To illustrate this, an example is taken from the survey. A set with various details is passed as input, e.g. age, gender and diagnosis. The aim is to determine, for example, whether a mouse-over function is helpful and whether pop-up elements are distracting or annoying. The attributes for the mouse-over function are "very helpful", "rather helpful", "I don't care", "don't know", "rather unhelpful", "not helpful" and "no answer" and for pop-ups these are "yes", "no", "don't know", "I don't care" and "no answer". A label is output for both properties, and each label is one of the possible classes of the corresponding property.

In order to make a feature selection, a correlation matrix was first created. This showed some strongly positive correlations. The matrix was therefore cut to values greater than 0.5. However, the correlations identified here were only of limited use in fulfilling the objective. For this reason, a different approach was chosen for the feature selection. For this purpose, all features (questions) were used and target variables were defined (59 in total). The target variables selected were the features that appeared relevant based on the correlations or were recognized as relevant questions in the workshops held at the beginning of the study.

The first step afterwards was to implement a for-loop that ran over the target variables so that all relevant features could be determined for each target variable. Then, within this for-loop, the target variable was removed from the main data set and the target column was determined. The two resulting data sets were divided again into training and test data with a ratio of 70%-30%. However, before the AI model could be trained with this data, the input training and test data sets had to be transformed using *OneHotEncoder*. In simple terms, this means that the categorical entries / strings were converted into a numerical array. The data sets were then scaled with the *RobustScaler* and converted into a DataFrame. These steps were necessary in order to be able to use the *accuracy_score function* later.

A *RandomForestClassifier* was then initialised with 100 decision trees and fitted with the training data sets, since in the literature the *RandomForestClassifier* has proven itself for a multiclass-multioutput classification problem (Hasan et al., 2016; Huljanah et al., 2019), as this supervised machine learning algorithm based on ensemble learning (Dong et al., 2020; Sagi and Rokach, 2018) is robust to overfitting and performs well on a variety of data sets. *RandomForestClassifiers* are widely used in practice due to their simplicity, effectiveness and ability to process high-dimensional data with a large number of features. For this type of algorithm, a large number of decision trees are constructed during training, and the mode of the classes (classification) of each tree is output. The final prediction is then made based on the ensemble learning method by summarizing the predictions of multiple decision trees. Briefly summarized, the method consists of the following 3 steps: random sampling, feature randomness and voting (Pal, 2005; Xu et al., 2012). In addition, the *MultiOutputClassifier* is required, which is used for multi target classification since it serves a a straightforward method to expand classifiers that lack built-in support for multi target classification. For this, it involves training one classifier for each target.

The *accuacy_score function* was then used to evaluate the accuracy of the model. In addition, the importance of the features for the target variable was plotted from "relevant" to "not relevant" (see Figure 5).

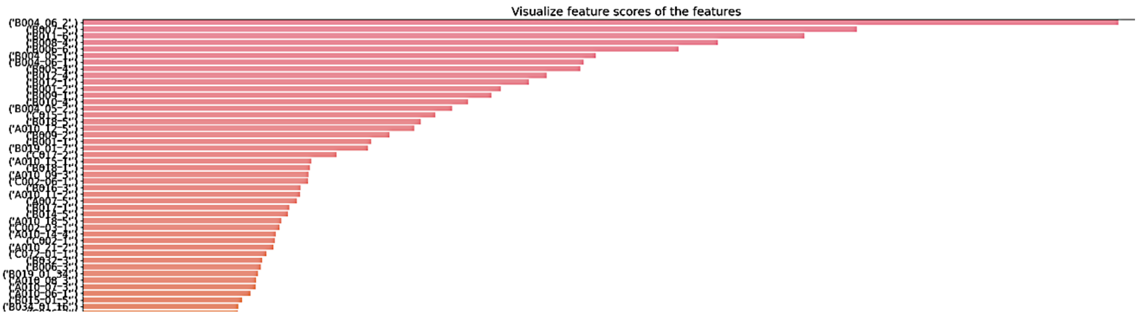

Figure 5. Exemplary Representation in the Form of an Excerpt for the Visualization of the Relevance of the Individual Features for a Target Variable

This showed that the accuracy of the individual models was between 0.2 and 1. Some target variables could therefore be predicted poorly and others very well.

Since the categorical entries are to be predicted and no numerical output is to be obtained at the end, an encoder cannot be used for the multiclass-multioutput classification problem. Therefore, the *TfidfVectorizer method* is used, which converts a collection of raw documents into a matrix of tf-idf (term frequency times inverse document frequency) features. The goal of using tf-idf instead of the raw frequency of occurrence of a token in a given document is to reduce the impact of tokens that occur very frequently in a given corpus and are therefore empirically less informative than features that occur in a small portion of the training corpus. After this method has been applied, the procedure is the same as described above: first the data sets are split into training and test data sets, the model is trained and the score is calculated.

If the input set is determined by only the most relevant feature for each target variable, the *RandomForestClassifier* with 100 decision trees in a multiclass-multioutput context produces a R^2 score of 0.0, as the data set is too small for this complex task. R^2 measures the proportion of variance in a data set that is described by a model. In the context of calculating R^2, variance is the deviation of observations from the mean. Subtracting a uniform number (mean or not) from the data has no effect on the pattern of deviation from the mean - it just shifts the mean. Since the selection of input features had no effect on the pattern of deviation from the mean, this means that the variances remaining after the selection are identical to those before the selection and divide to 1. As no difference was made to the variance, R^2 is 0.0. This score represents a model that does not explain any of the variation in the response variable around its mean.

The target variables were therefore reduced to the questions that had achieved an accuracy of 1 and the remaining questions were used as input variables. This resulted in 3 variables as target variables and yielded a score greater than 0.96 for the model. The target variables for which the model had achieved an accuracy of >0.9 were then added. This yielded a score of 0.88 for the model. For comparison and validation, 3 target variables were selected for which the model had only achieved an accuracy of approx. 0.2. This resulted in a score of just 0.038 for the model in the multiclass-multioutput context. It can therefore be seen that great attention must be paid to correlations in feature selection, which is a challenge in this context.

This first approach shows that AI cannot only be used to obtain favored elements more quickly during the evaluation, but also to reduce the set of questions to be asked and still increase the quality of the UI to be implemented.

5.2 Results and Discussion

As this research is a complex and extensive task, only extracts of the results are presented in this paper. These focus on the W3C Working Group Note (W3C, 2021) to prove or disprove it respectively to argue that there is a need to differentiate between cognitive and learning disabilities and neurodivergence/neurodivergent traits, and to show the benefits of using AI in UI design.

As best practices, the W3C Working Group Note (W3C, 2021) recommends that designers should *"[..]support different ways to understand content"*. However, this must be approached sensitively, as it can quickly lead to excessive workload and sensory overload with corresponding consequences, such as meltdowns. Neurodivergent people are much more prone to this than neurotypical people (see Figure 6).

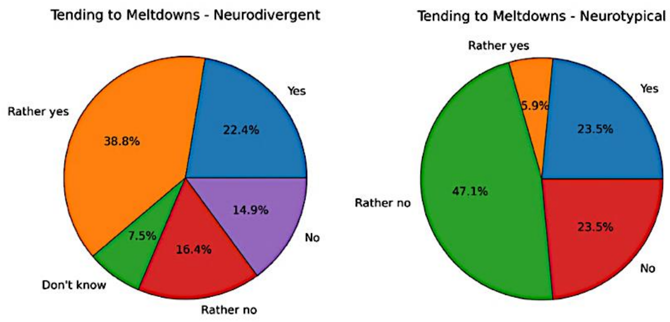

Figure 6. Depiction of the Tendency to Meltdowns Distinguished between Neurodivergent and Neurotypical Persons among the Professional Sectors IT, Production, Mechanical Engineering and Technology

Furthermore, in section 3.1.3 *"I need symbols placed above the text to link the meaning of the words with the images"* is cited as a user story for people with complex communication needs, which includes autistic people and people with ADHD. However, the survey shows that neurodivergent people prefer either this or to the left from the text. Neurotypicals, on the other hand, clearly favor left from the text, meaning that this design suggestion is not necessarily conducive to a neurodiverse-friendly design (see Figure 7). Based on these results, it is recommended that icons be placed to the left of the text for a neurodiverse-friendly UI design.

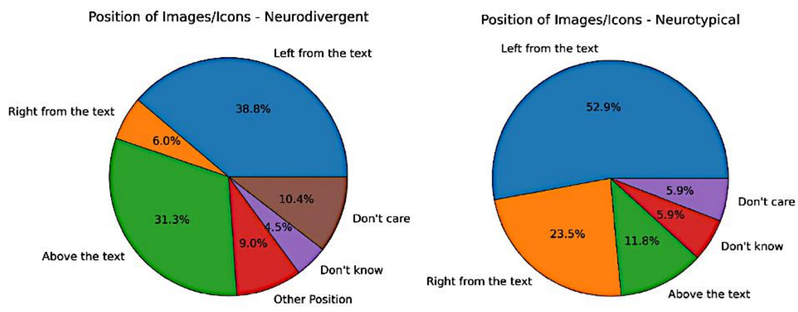

Figure 7. Depiction of the Position of Images/Icons Distinguished between Neurodivergent and Neurotypical Persons among the Professional Sectors IT, Production, Mechanical Engineering and Technology

The user story in section 3.3.2 *"I need a good use of white spaces, so that the chunks are clear and the page does not get overwhelming"* was largely confirmed. However, care must again be taken here to ensure that there is not too much white space, as this can be distracting, especially for neurodivergent users (see Figure 8).

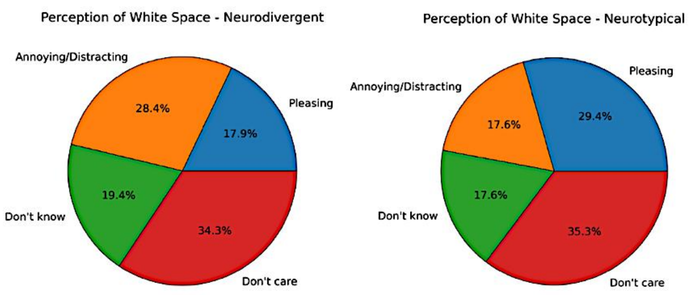

Figure 8. Perception of the Usage of White Space in UI Design Distinguished between Neurodivergent and Neurotypical Persons among the Professional Sectors IT, Production, Mechanical Engineering and Technology

This should therefore always be scaled in such a way that it serves clear arrangement, scalability and scanability, as these areas are (rather) important for 90-100% of both neurodivergent and neurotypical participants. Similar applies to the unambiguousness of the UIs (80-93%) and the logical structure (100%). The study also showed that contrast is very or rather important for 92% of neurodivergents, compared to only 71% of neurotypicals. However, this shows that more attention needs to be paid to the topic of contrast in the style guides, as rejection of the system is not unlikely. The W3C

Working Group Note (W3C, 2021) also does not devote sufficient attention to the topic of fonts. For 77% of neurodivergents, for example, the font is of fundamental importance. In comparison, this only applies to 53% of neurotypicals. However, both groups agree (about 85% both) that the font must be simple and clear, such as the Verdana font, and that the font for a DIN A4 printout should be between 10 and 14 (82-90%).

It was also confirmed that telephone numbers or credit card numbers should be written separately, e.g. space between area code and actual number (see section 3.4.1 in (W3C, 2021)). As this is favored by over 80% of both neurodivergents and neurotypicals, this design proposal is advantageous for a neurodiverse-friendly design.

The user story *"I need a login process that does not have puzzles or calculations."* in section 3.6.2 could also be verified in a transferred sense. The majority of participants of both groups would like to abandon captcha codes (about 55%) or do not care (nearly 24% of neurotypicals).

The W3C Working Group Note (W3C, 2021) lists the user story *"I need text-to-speech support, with synchronised highlighting, so I can follow along as words are read aloud."* in section 3.7.2 for people with ADHD. The results of the study contradict this assumption. The majority of both groups (51% of neurodivergents and 65% of neurotypicals) do not want this function. Only 15% and 12% respectively would like it. This shows how challenging it is to create a universal style guide for inclusive design.

Section 4.4.1.4 recommends using pop-up definitions to provide explanations for unknown words and the like. However, this is not advisable, as pop-ups are particularly distracting for neurodivergent people. This obstacle should be overcome using mouse-overs (see Figure 9).

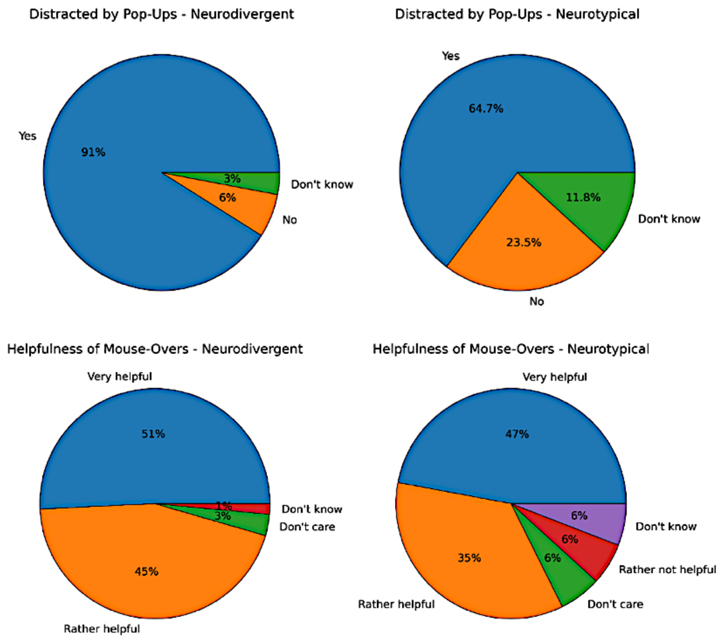

Figure 9. Distraction by Pop-Ups and Usage of Mouse-Overs in UI Design Distinguished between Neurodivergent and Neurotypical Persons among the Professional Sectors IT, Production, Mechanical Engineering and Technology

As noted, the results presented here represent only a part of the study. However, they already provide initial indications that further research is needed in this area and, above all, that neurodivergents should not be grouped together with people with cognitive and learning disabilities. More differentiated analyses need to be carried out here in order to enable or positively support a neurodiverse-friendly design. To summarize these results for a first design recommendation, it can be stated that a possible sensory overload of the user and the associated consequences such as meltdowns should be avoided and therefore UIs should not be overloaded. Therefore, (additional) information should be presented in a way that does not distract the user, e.g. via mouse-overs. Since the majority of neurodivergent users do not perceive themselves as disabled or (cognitively) impaired, the UI should be designed to support them in their work, but not to patronize them. The use of assistants such as *Clippit* (Office Assistant) or chatbots should therefore be carefully evaluated and, if necessary, implemented in such a way that they need to be actively triggered in order to receive help. Furthermore, future style guides must pay more attention to the areas of clear arrangement, scalability, scanability, unambiguousness, logical structure, contrast, and fonts and their concrete implementation in their recommendations.

The model presented in the previous section was used as an example for mouse-overs and pop-ups. For this purpose, the corresponding features for mouse-over and pop-up were selected as target variables. Although the model only achieved a score of 0.42, mouse-over was predicted to be "rather helpful" and pop-up "yes" (i.e. distracting). In the direct analysis, the majority of mouse-overs were "very helpful", but the difference was only minimal. This once again emphazises the benefits of using AI, even if there is still a need for adjustment in terms of feature selection and model configuration.

6 Limitations

The methodology described here is limited in a few ways. On the one hand, the used data set is relatively small with a total of 84 participants for the training of AI, and on the other hand, it is also unbalanced with regard to neurodivergent and neurotypical participants (80%-20%). Various additional data pre-processing steps, such as data augmentation, must be applied in further studies as well as the whole data set with 222 participants has to be used. Another limitation is the feature selection. Since this procedure is a multiclass-multioutput classification problem, simple known feature selection methods are not easy to apply. Therefore, the current selection of features was based both on simple correlations and on the information from the workshops as described in section 2.1. The number of decision trees must also be evaluated and adjusted if necessary. In general, more in-depth evaluations must also be carried out. For example, all questions must be evaluated for each type / combination of neurodivergence in order to obtain a meaningful picture or to recognize overlaps.

The confidence intervals also show that the results can only be generalized to a limited extent. As the population in the professional sectors IT, production, mechanical engineering and technology is not known with regard to the number of neurodivergent and neurotypical employees, the standard calculation with a sample size of 67 people results in a margin of error of approx. 10% for neurodivergents at a 90% confidence level. The result for neurotypicals is less acceptable, as there is a margin of error of approx. 8% for a sample size of 17 people, but the confidence level here is only 50%. With a confidence level of 90%, the margin of error would be 20%. In addition, many cases are misdiagnosed or not recognized. This is a particular problem for women (Waite, 2007). As a result, it cannot be said with certainty that neurotypical people are really neurotypical.

7 Conclusion and Future Work

The study presented here shows that previous research on UI design for neurodivergent users is either almost non-existent or still incomplete. The analysis of the survey also showed that neurodivergent people cannot be equated with people with cognitive and learning disabilities. A nuanced approach is therefore needed to design neurodiverse-friendly UIs for IT-systems. It is also important that highly-gifted people are taken into account in the future. In addition, the use of AI presented here has shown promising results.

However, the study has shown that neurotypical and neurodivergent people are more likely to have the same needs, but that the existing style guides are not precise enough in their recommendations and therefore do not meet the needs of both groups in practical implementation. Therefore, not only does a deeper study between the groups need to be conducted to identify possible differences, but the depth and accuracy of the style guides also needs to be adjusted.

The next step is to look at the various neurodivergent groups, including highly-gifted individuals. This will involve a more detailed analysis of the survey. In addition, the needs of the genders should also be considered in order to identify any differences here as well. Further data pre-processing steps, such as data augmentation, need to be carried out and other methods of feature selection for a multiclass-multioutput classification problem need to be evaluated as well as the number of decision trees for the *RandomForestClassifier*. Furthermore, an attempt will be made to collect more data in order to extend and increase the existing data set to make it more suitable for training an AI model.

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References

Austin, R. D. and Pisano, G. P., 2017. Neurodiversity as a competitive advantage, Harvard Business Review, 95(3):96–103, 2017. doi: https://doi.org/10.4324/9781003434610-3

Brinzea, V., 2019. Encouraging Neurodiversity in the evolving workforce - The next frontier to a diverse workplace, Scientific Bulletin-Economic Sciences/Buletin Stiintific-Seria Stiinte Economice, 18(3), doi: https://doi.org/10.1017/iop.2022.86

Bruyère, S. M. and Colella, A. eds., 2022. Neurodiversity in the workplace: Interests, issues, and opportunities. Taylor & Francis.

Dong, X., Yu, Z., Cao, W., Shi, Y. and Ma, Q., 2020. A survey on ensemble learning. Frontiers of Computer Science, 14, 241-258. doi: https://doi.org/10.1007/s11704-019-8208-z

Doyle, N., 2022. Adapting Other Internal Organizational Resources to a Neurodiverse Workforce, in: Bruyère, S. M. and Colella, A. eds., 2022. Neurodiversity in the workplace: Interests, issues, and opportunities. Taylor & Francis, p. 274, doi: https://doi.org/10.4324/9781003023616-11

Genaro Motti, V. G., 2019. Designing emerging technologies for and with neurodiverse users, Proceedings of the 37th ACM International Conference on the Design of Communication, pages 1–10. doi: https://doi.org/10.1145/3328020.3353946

Hasan, M. A. M., Nasser, M., Ahmad, S. and Molla, K. I., 2016. Feature selection for intrusion detection using random forest. Journal of information security, 7(3), 129-140. doi: https://doi.org/10.4236/jis.2016.73009

Houdek, P., 2022. Neurodiversity in (not only) public organizations: an untapped opportunity?. Administration & Society, 54(9), 1848-1871. doi: https://doi.org/10.1177/00953997211069915

Huljanah, M., Rustam, Z., Utama, S. and Siswantining, T., 2019. Feature selection using random forest classifier for predicting prostate cancer. In IOP Conference Series: Materials Science and Engineering (Vol. 546, No. 5, p. 052031). IOP Publishing. doi: https://doi.org/10.1088/1757-899x/546/5/052031

Kamaruzaman, M. F., Rani, N. M., Nor, H. M. and Azahari, M. H. H., 2016. Developing user interface design application for children with autism. Procedia-Social and Behavioral Sciences, 217, 887-894. doi: https://doi.org/10.1016/j.sbspro.2016.02.022

Keil, M. V. and Bleisinger, O., 2023. Benutzeroberflächen von MBSE-Tools und deren Auswirkung auf neurodivergente Systemarchitekten, Proceedings of Tag des Systems Engineering 2023, pp. 9-15

Kittel-Schneider, S., Arteaga-Henriquez, G., Vasquez, A. A., Asherson, P., Banaschewsk, T., Brikell, I. et al., 2022. Non-mental diseases associated with ADHD across the lifespan: Fidgety Philipp and Pippi Longstocking at risk of multimorbidity?, Neuroscience & Biobehavioral Reviews, 132, pp.1157-1180. doi: https://doi.org/10.1016/j.neubiorev.2021.10.035

Lukava, T., Morgado Ramirez, D. Z. and Barbareschi, G., 2022. Two sides of the same coin: accessibility practices and neurodivergent users' experience of extended reality. Journal of Enabling Technologies, 16(2), 75-90. doi: https://doi.org/10.1108/jet-03-2022-0025

Mai, L. T., Gollasch, D., Boß, C. and Werdin, H., 2023. Transferring Real Operating Concepts Into Virtual Reality for Neurodiverse Learners.

Matejcek, A., 2017. Influence: Art, Activism, and Identity as Seen Through a Neurodivergent Lens. doi: https://doi.org/10.18122/b2q40h

Mejıa-Figueroa, A. and Juarez-Ramirez, J., 2015. Defining an interaction model for users with autism: Towards an autistic user model, In International Conference on Universal Access in Human-Computer Interaction, pages 626–636, Springer. doi: https://doi.org/10.1007/978-3-319-20684-4_60

Ntalindwa, T., Nduwingoma, M., Karangwa, E., Soron, T. R., Uworwabayeho, A., Uwineza, A., et al., 2021. Development of a mobile app to improve numeracy skills of children with autism spectrum disorder: Participatory design and usability study, JMIR pediatrics and parenting, 4(3):e21471. doi: https://doi.org/10.2196/21471

Orsini, M., 2012. Autism, neurodiversity and the welfare state: The challenges of accommodating neurological difference, Canadian Journal of Political Science/Revue canadienne de science politique, 45(4), pp. 805-827. doi: https://doi.org/10.1017/s000842391200100x

Pal, M., 2005. Random forest classifier for remote sensing classification. International journal of remote sensing, 26(1), 217-222. doi: https://doi.org/10.1080/01431160412331269698

Pandian, V. P. S. and Suleri, S., 2020. BlackBox Toolkit: Intelligent Assistance to UI Design. arXiv preprint arXiv:2004.01949.

Pavlov, N., 2014. User Interface for people with autism spectrum disorders, Journal of Software Engineering and Applications. doi: https://doi.org/10.4236/jsea.2014.72014

Prawira, G. S. A., Kaburuan, E. R. and Effendy, V., 2017. User interface (UI) design of scheduling activity apps for autistic children. In 2017 International Conference on Orange Technologies (ICOT) (pp. 129-133). IEEE. doi: https://doi.org/10.1109/icot.2017.8336105

Sagi, O. and Rokach, L., 2018. Ensemble learning: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1249. doi: https://doi.org/10.1002/widm.1249

Spiel, K. and Gerling, K., 2021. The purpose of play: How hci games research fails neurodivergent populations, ACM Transactions on Computer Human Interaction (TOCHI), 28(2):1–40. doi: https://doi.org/10.1145/3432245

Soward, W., 2024. Neurodiversity Design System, https://neurodiversity.design

Thesmann, S., 2016. Interface design, Springer Fachmedien, Wiesbaden.

W3C, 2021. Making Content Usable for People with Cognitive and Learning Disabilities, W3C Working Group Note 29 April 2021, https://www.w3.org/TR/2021/NOTE-coga-usable-20210429/

Waite, R., 2007. Women and attention deficit disorders: A great burden overlooked. Journal of the American Association of Nurse Practitioners, 19(3), 116-125. doi: https://doi.org/10.1111/j.1745-7599.2006.00203.x

Weber, C., Krieger, B., Häne, E., Yarker, J. and McDowall, A., 2022. Physical workplace adjustments to support neurodivergent workers: A systematic review, Applied Psychology. doi: https://doi.org/10.1111/apps.12431

Wyrsch, P. C., de Groote, J. K. and Hack, A., 2020. Hoch (neuro) sensitive Mitarbeitende: Weicheier oder Wunderkinder?, Bern Open Publishing.

Xing, B., Cao, H., Shi, L., Si, H. and Zhao, L., 2022. AI-driven user aesthetics preference prediction for UI layouts via deep convolutional neural networks. Cognitive Computation and Systems, 4(3), 250-264. doi: https://doi.org/10.1049/ccs2.12055

Xu, B., Guo, X., Ye, Y. and Cheng, J., 2012. An improved random forest classifier for text categorization. J. Comput., 7(12), 2913-2920. doi: https://doi.org/10.4304/jcp.7.12.2913-2920 7

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