EXTENDED-ABSTRACT

# User-controlled Form Adaptation by Unsupervised Learning

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# User-controlled Form Adaptation by Unsupervised Learning

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## ABSTRACT

Forms are one of the most popular and widespread methods of interaction, yet they remain largely improper for adaptation. We argue that forms should be adapted to the user and their context in a controllable way, to minimize the potential negative effects of any adaptation. This can be accomplished with Scaler, a novel web environment for designing and deploying forms in which adaptation is initiated by the system and/or the user according to a vector profile, but always under the user's control, using two unsupervised learning methods: (1) A scoring function that ranks the most usable widgets for each data item on the form, balancing the input and preferences of the stakeholders involved in the form (i.e., user, designer, and developer). (2) A widget recommendation that contrasts the user's profile and those of all other users who have used the same form, whether they have modified it before or not. Our experiment with a car booking form shows that, after some interaction sessions (from 1 to 50 depending on the form field) and some user-controlled adaptations (from 3 to 29 depending on the field), the form design converged to a stabilized selection.

## CCS CONCEPTS

• **Social and professional topics** → **Software selection and adaptation**; • **Computing methodologies** → *Ranking*; • **Human-centered computing** → **Graphical user interfaces**; *Interactive systems and tools*; User interface design.

## KEYWORDS

Adaptivity, Adaptive user interfaces, Form design, User control.

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## 1 INTRODUCTION

Adapting user interfaces is an essential practice in user interface design to create intuitive, efficient, and user-friendly experiences [1, 3]. By tailoring *Adaptive User Interfaces* (AUIs) [12] to meet the specific needs [18] and preferences of users [21] in their contexts of use [33, 44], we can improve usability, user experience [30], and accessibility [39], leading to engagement and satisfaction [45].

AUIs have long been studied [12] and implemented [16], being convinced that they would achieve their objective by relying on adaptation rules involved either at design-time [2, 40] or at run-time [5], using for example grammars [11, 19], specification languages [8], model-based design approaches [5, 20, 30], model-driven approaches [2, 8, 27], and model-free approaches [35, 36]. This approach has nurtured the illusion that a sufficiently large number of adaptation rules will result in an AUI that demonstrates real accuracy [22] to adapt to the user's context [17, 30, 44], a real maximization of quality factors while minimizing potentially negative effects such as disruption [29]. Adding new rules no longer serves any purpose, except to lead to new exceptions, contradictions against previous rules, and complexity in managing them.

The UI adaptation process is a multi-factorial phenomenon: it is virtually impossible to know all the conditions under which a good adaptation rule applies to produce a positive result. Too many heterogeneous factors are intertwined to guarantee a positive outcome. For example, Lavie and Meyer [33] showed that the cost of an AUI can exceed the expected benefit. Only a few of these factors are known, such as personal traits and cognitive load [21], and too few to generalize their application. In particular, the end user may well expect an AUI, but it fails to do its job because neither preference nor performance are met [3]. The main cause of these shortcomings lies in the absence—or lack of consideration—of user feedback [53] and control [15, 28] throughout the adaptation life cycle. Yet, there are many opportunities within the user's control [9] where they could intervene to steer the process in the right direction (e.g., [16] and [37] identified four and seven adaptation stages, respectively) or, at the very least, avoid undesirable or inappropriate adaptations. Langley [32] has long recommended the use of Machine Learning (ML) so that the AUI learns how to adapt under the control of the end user, rather than imposing an adaptation whose outcome is not guaranteed. However, the practical implementation of ML is proving to be more complex than expected [4, 51, 54], since a large number of samples and participants are required [41], different characteristics must be mastered, and it is not clear which adaptation rules should evolve and how.

To address these shortcomings, we propose Scaler (uSer- Controlled Adaptation of Forms by Unsupervised Learning), a web environment for deploying adaptive forms under the user's control thanks to two unsupervised learning methods: a scoring function and a widget recommendation. We ran a user study showing that progressive convergence stabilizes the adaptation to a favored selection. Our work can inform future research on AUIs and related areas.


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## 2 RELATED WORK

In the area of AUIs, *adaptive forms* represent a proven approach to enhancing user experience [30] by dynamically adjusting form widgets based on the context of use [44], which incorporates the end user's profile and the associated interactive tasks, the platform or device used to interact, and the environment in which this interaction takes place [13, 40]. Adaptive forms have been used in many practical domains, such as accounting [2], healthcare [18], municipal administration [31], multimodal systems [5, 27, 50], mobile devices [43], and business processes [46]. ML has been used for adaptation in teaching [4] and multi-screen interaction [47].

DynaForms [24], MasterMind [19] and FormGen [11] all defined a context-free grammar to specify adaptive forms, in which form fields are described using tuples (records), variants, lists, and basic predefined types to be mapped to widgets according to selection rules [6, 49]. Although these selection rules can be modified and extended at design-time, they cannot produce adaptive results at run-time, therefore preventing the form from benefiting from adaptivity gains. Similarly, AdapForm [7] promotes a form definition language that designates the structure and constraints upon acceptable input, and a software architecture that continuously validates and adapts the form. While the state of the form is kept persistently on the server side, the system ensures that all forms are valid and type safe, thereby making them helpful [8].

Other approaches use an XML-based specification of the adaptive form [8], such as xForms [27], and structured models [2, 5]. While these specifications and models are interpreted at run-time, therefore making forms rather flexible for adaptation, they do not involve any form of user control during adaptation. As a workaround, animated transitions [15] let the user see and understand the adaptivity process. However, this study suggests that end-users no longer request any such animated transition after gaining trust.

PowerForms [10] exploits JavaScript to validate user input on the client side in HTML forms: it generates an interactive form that combines static HTML form and a PowerForms specification that performs continuous validation as the form is filled. Adaptive forms should leverage data-driven personalization to enhance the user experience. By analyzing the user's interaction history, preferences, and behavior patterns, forms can be adapted to present relevant fields and options in a more personalized way [14, 38]. Adaptive forms often embed real-time feedback mechanisms to guide users as they fill out fields. Immediate validation and error messages help users correct errors on the fly, preventing frustration and enhancing the user experience. Advanced techniques, such as predictive text and contextual hints, can also be used to assist users in providing accurate information, further streamlining the process. To this end, the integration of ML into adaptive forms (using multi-class classification [51], spatio-temporal structure learning [34], or reinforcement learning [54]) represents a significant advancement, as ML can analyze user behavior in real-time to predict and suggest accurate [22] adaptation of fields, auto-complete information, and adapt the complexity of the layout based on the user's expertise level. For example, a novice user might see a simplified form, while an expert user receives a more detailed version [2]. In sum, adaptive forms existed for a while, but without user control, ML techniques have recently been considered to support form adaptation.

## 3 USER-CONTROLLED FORM ADAPTATION

Fig. 1 shows a system walkthrough of Scaler on a car rental UI, a W3C reference case study [42]: ① the user creates and edits the specifications of form fields in terms of data type, format, domain of values, input method (e.g., by typing or selecting), and constraints. Using these specifications, Scaler automatically selects relevant Abstract Interaction Objects [49] that can be reviewed and edited by a designer based on design experience or the end user based on preferences; ② the resulting form is rendered in HTML5.

To make the form adaptive, Scaler enables the end user to specify a scoring function ③ and/or to rely on a recommendation mechanism ④, using two unsupervised learning methods that consider three profiles: *anonymous users* (since they are not authen-ticated, they can provide Scaler with feedback and adapt the form to their purpose, thereby feeding the global system, but their adaptation will be lost for them), *identified users* (since they are authenticated, they benefit from all unsupervised learning to adapt their forms), and *administrators* (they are authenticated designers, developers, or super-users who can create, edit, and delete any form). An administrator can also assign a role to any other user, such as "writer", "translator", or "manager".

### 3.1 Unsupervised Learning by Scoring

Scaler calculates a score for adapting each widget corresponding to any form field to the context of use, then selects and displays the widget with the highest score. If the user wants to change the selected widget (via the Change widget push button), the list of other widget proposals is sorted in descending order of their score based on four sub-scores:

(1) *Score of Change* (*SC*): a score assigned to a widget chosen by the end-user when it was not the default widget (i.e., it was not the widget with the highest score).
(2) *Score of Unchange* (*SU*): a score assigned to a widget chosen by the end user when it was the default widget (i.e., the widget that received the highest score).
(3) *Score of Admin* (*SA*): a score assigned to a widget chosen by the administrator as the default choice, assuming that the selection is not randomly performed.
(4) *Score Global* (*SG*): an overall score assigned to all widgets of this type when any of them is selected. For this purpose, a list of potential widgets is assigned to any Abstract Interaction Object (AIO), which corresponds to one type (see ② in Fig. 1).

To determine these scores, we define three system variables for every widget of every form:

(1) *Number of Changes* ($C$): the number of times a widget has been chosen by the end-user when it was not the default widget.
(2) *Number of Unchanges* ($U$): the number of times a widget has been chosen by the end-user when it was already the default widget.
(3) *Number of Global Choices* ($G$): the number of times a widget of this type has been chosen by end users.

Since these variables are specifically tailored to every widget of every form, their values and treatments can largely vary from one form to another. Scaler captures the context of use (e.g., the user ID

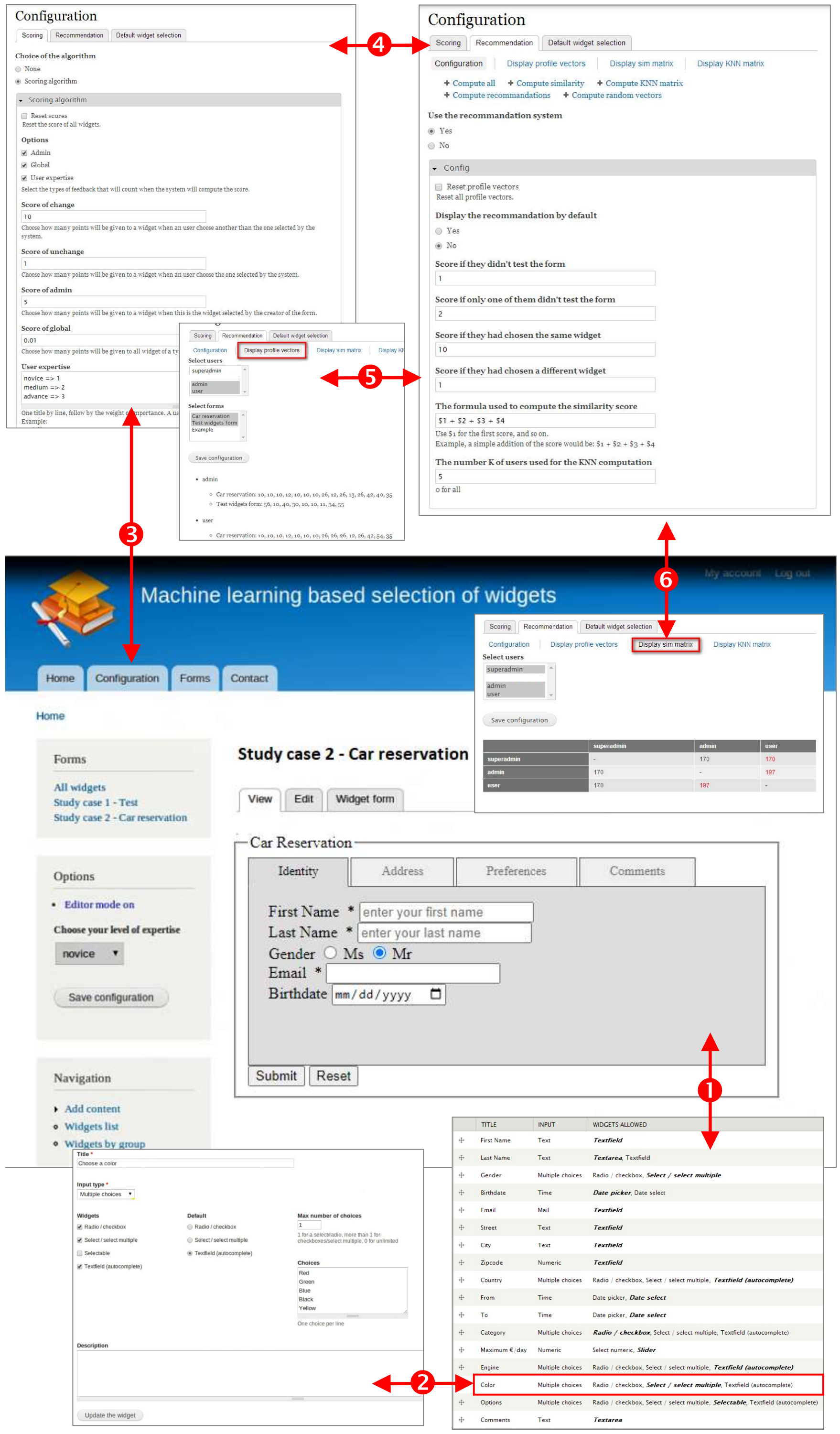



**Figure 1: SCALER system walkthrough: ① editing the specifications of form fields and direct rendering, ② connecting to an abstract interaction object, ③ specifying a scoring function, ④ defining the recommendation mechanism, ⑤ displaying the vector profile of a user, and ⑥ accessing the similarity matrix.**

$$\text{scoring}\,(w, form) = \begin{cases} C \times SC + U \times SU + G \times SG & \text{if Admin=false and Global=false} \\ C \times SC + U \times SU & \text{if Admin=false and Global=true} \\ C \times SC + U \times SU + f(w, SA) & \text{if Admin=true and Global=false} \\ C \times SC + U \times SU + G \times SG + f(w, SA) & \text{if Admin=true and Global=true} \end{cases}$$

**Figure 2: Definition of the scoring function.**

or the height and width of the screen) and the system variables in a hidden text area included in each form: all actions and events are captured via W3C Window Object and W3C Navigator Object, and stored as a log file on the server side, with a timestamp. For example, Fig. 3 shows the adaptation history of a form containing two widgets that have been adapted recently on a Windows platform having a resolution of 1200 × 920 pixels, browsed through various browsers, such as Safari. This log file is exploited at run-time for performing adaptation operations and is, therefore, not directly visible to the eyes of the end-user. This log file is also exploited to determine which widget(s) have already been selected in the past, if any, in order not to repeat the same selection: the rendering of the log file shows the most suitable widgets in decreasing order of prediction either in a generic way (when no adaptation has been yet performed) or in a specific way (when some adaptation has been recorded in this history). This log file is specific for every form for every user: another user using the same form may result to a completely different log file, even if the selection of widgets remains the same in the end. Scaler keeps track of the hidden textarea and exploits it for adaptation in a scoring function.

A *scoring function*, also referred to as an objective function, is used in optimization problems to evaluate the performance or the quality of a model's predictions or solutions [41]. We define the Scaler scoring function in Fig. 2 depending on the parameters selected (③ in Fig. 1), where $f(w, SA) = SA$ if the widget $w$ was the default widget selected by Scaler or the designer or 0 otherwise. The end user then (un)checks the parameters of this scoring function depending on the adaptation needs and preferences.

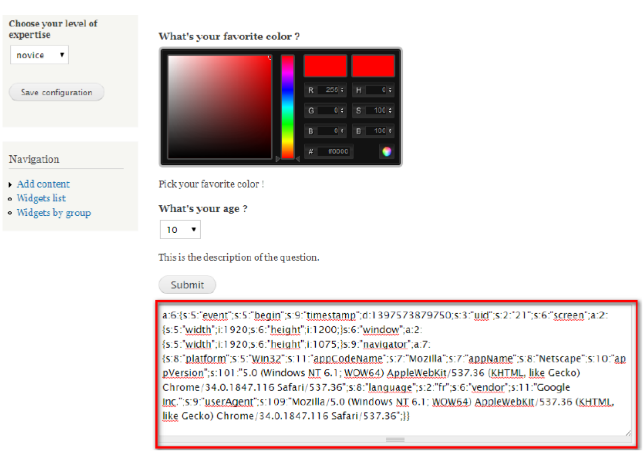



**Figure 3: Scaler's textarea for recording and storing form actions, events, and its context of use.**

## 3.2 Unsupervised Learning by Recommendation

The second method consists of applying the $k$-nearest neighbors ($k$-NN) algorithm, a non-parametric, unsupervised learning classifier using proximity to make predictions about the grouping of an individual object or 'data point'. We assume this is the case for any user who will be near other users of the same form, either in similar or different contexts of use.

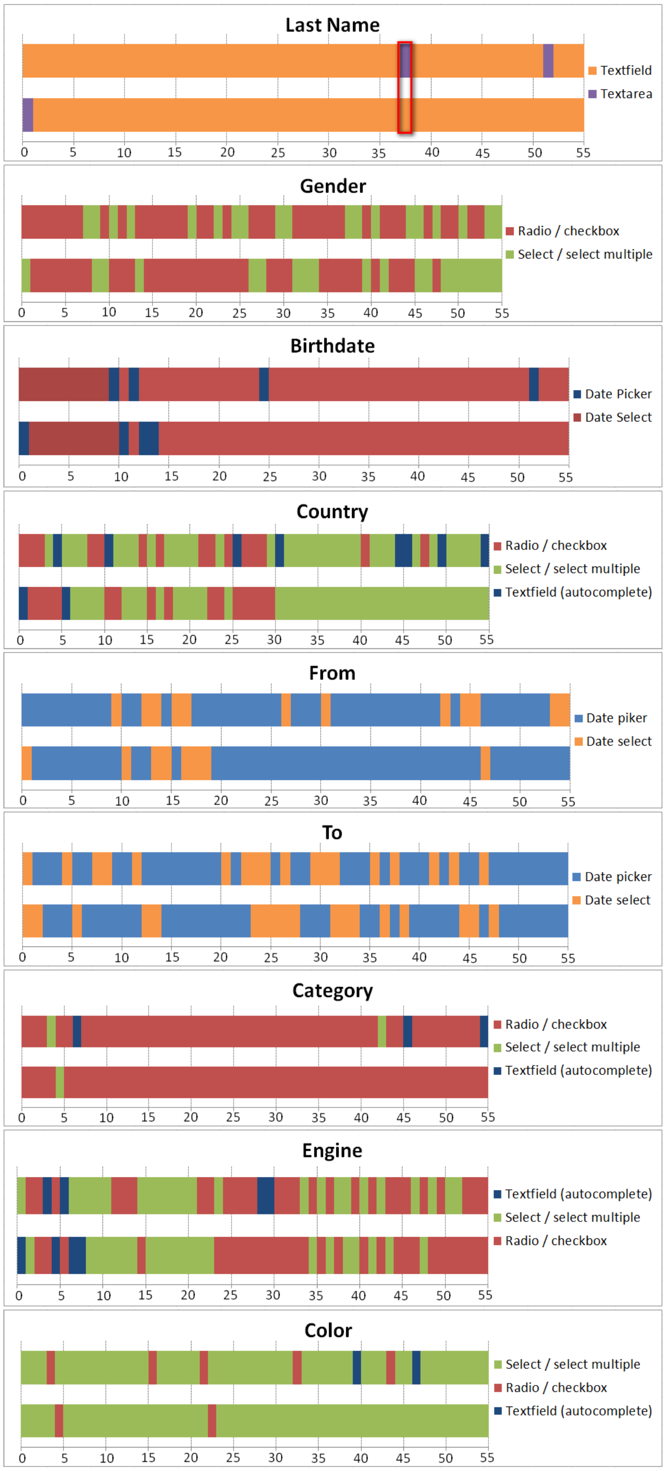
This method is typically used to classify an object with respect to a class of objects among its $k$ nearest neighbors [26] The underlying assumption in $k$-NN is that similar objects can be found near each other. In 1-NN, its simplified version with $k$=1, the candidate object is simply assigned to the class of the closest neighbor. Scaler uses a 1-NN to determine suitable recommendations for each user (④ in Fig. 1). For this purpose, a user vector profile is created to express their preferences for interaction and for the available widgets to investigate similarities between users (⑤ in Fig. 1): an indexed vector referring to a set of available widgets where "0" indicates that an existing widget has never been used, "1" indicates a widget used, and "-1" is used to indicate new widgets.

A similarity matrix is dynamically created to identify common user profiles (⑥ in Fig. 1). In this matrix, the value of a point $(i, j)$ is the Euclidean distance between $i$ and $j$. Once the similarity index is calculated and the $k$ nearest profile is determined, a prediction value is computed by widget, as a recommendation for the user. The prediction score of a widget $j$ to a user $i$ is calculated as the sum of the widget frequencies for users, weighted by the similarity of the users $a_{pj}$ (Fig. 4). Similarly to the scoring function presented in the previous section, the weights representing the various types of users can be adjusted to reflect their relative importance. For example, if the designer's choice is considered the most important, its corresponding weight can be increased by decreasing the weight for another user or developer.

k-NN based selection of a widget

**let** $D \leftarrow$ the set of $k$ training profiles
**let** $p \leftarrow$ the test user profile
**let** $W \leftarrow$ the set of adapted widgets
**for** *each* $p \in D$ **do**
  $d(p, p') \leftarrow$ distance (p, p')
  $\mathcal{A}$ = frequency matrix where $a_{ij}$=(user, widget)
**end**
**let** $D_k \subseteq D$ the set of $k$ closest training objects for $p$
**return** *ScorePrediction* (p,j) = $\frac{\sum_{p=1}^{k} sim(i,p) \times a_{pj}}{\sum_{p=1}^{k} sim(i,p)}$

**Figure 4: Algorithm for computing prediction score.**




| Selected vs. Pred. | Textfield | Textarea | Total |
|---|---|---|---|
| Textfield | 52 | 1 | 53 (96.4%) |
| Textarea | 2 | 0 | 2 (3.60%) |
| Total | 54 | 1 | 52 (94.5%) |

| Selected vs. Pred. | Radio | Select | Total |
|---|---|---|---|
| Radio | 21 | 15 | 36 (65.5%) |
| Select | 14 | 5 | 19 (34.5%) |
| Total | 35 | 20 | 26 (47.3%) |

| Selected vs. Pred. | Date picker | Date select | Total |
|---|---|---|---|
| Date picker | 0 | 4 | 4 (7.3%) |
| Date select | 4 | 47 | 51 (92.7%) |
| Total | 4 | 51 | 47 (85.5%) |

| Selected vs. Pred. | Radio | Select | Auto. | Total |
|---|---|---|---|---|
| Radio | 6 | 8 | 1 | 15 (27.3%) |
| Select | 6 | 25 | 1 | 32 (58.2%) |
| Autocomplete | 3 | 5 | 0 | 8 (14.5%) |
| Total | 15 | 38 | 2 | 31 (56.4%) |

| Selected vs. Pred. | Date picker | Date select | Total |
|---|---|---|---|
| Date picker | 37 | 6 | 43 (78.2%) |
| Date select | 10 | 2 | 12 (21.8%) |
| Total | 47 | 8 | 39 (70.9%) |

| Selected vs. Pred. | Date picker | Date select | Total |
|---|---|---|---|
| Date picker | 24 | 13 | 37 (67.3%) |
| Date select | 13 | 5 | 18 (32.7%) |
| Total | 37 | 18 | 29 (52.7%) |

| Selected vs. Pred. | Radio | Select | Auto. | Total |
|---|---|---|---|---|
| Radio | 49 | 1 | 0 | 50 (90.9%) |
| Select | 2 | 0 | 0 | 2 (3.6%) |
| Autocomplete | 3 | 0 | 0 | 3 (5.5%) |
| Total | 54 | 1 | 0 | 49 (89.1%) |

| Selected vs. Pred. | Textarea | Select | Radio | Total |
|---|---|---|---|---|
| Textarea | 0 | 0 | 4 | 4 (7.3%) |
| Select | 3 | 10 | 11 | 24 (43.6%) |
| Radio | 1 | 12 | 14 | 27 (49.1%) |
| Total | 4 | 22 | 29 | 24 (43.6%) |

| Selected vs. Pred. | Select | Radio | Textarea | Total |
|---|---|---|---|---|
| Select | 46 | 2 | 0 | 48 (87.3%) |
| Radio | 5 | 0 | 0 | 5 (9.1%) |
| Textarea | 2 | 0 | 0 | 2 (3.6%) |
| Total | 53 | 2 | 0 | 46 (83.6%) |

**Figure 5: Some scarf plots and confusion matrices of our case study.**

## 4 USER STUDY

We conducted a user study with 55 randomly selected participants (50 male, 5 female) from our institution's mailing lists, Participants were 18–50 years old (M=24 years) and had different expertise levels in using forms (novice, intermediate, and expert). After a brief introduction to the study, the participants were instructed to use the car rental UI to complete a reservation, allowing them to adapt the forms according to their preferences. Participants were granted user access to SCALER so that they could adapt the forms from their own browser. Fig. 5 shows the results of the adaptation process as a scarf plot [52] (left) and a confusion matrix (right). For example, the Last name field was subject to selection to a textfield or a textarea: one user adapted a textfield to a textarea and two users used a textarea without changing it. Similar figures are obtained for all form fields. We observe a progressive convergence that stabilises the adaptation on the most preferred selection of widgets: after some adaptation and some time, users no longer required any adaptation from SCALER.

## 5 CONCLUSION AND FUTURE WORK

We have presented SCALER, a web environment for designing and deploying forms in which adaptation is initiated by the system and/or the user under the user's control, using two unsupervised learning methods: a scoring function and a recommendation algorithm. While the end user is indeed able to control the adaptation process, namely by choosing the learning method and parameterizing it, further experimentation is desired to investigate which method they prefer and how they determine the weights according to their preferences, which is a multi-factorial and elusive problem. The future of adaptive forms and AUIs lies in further advancements in ML, such as with reinforcement learning [48, 54], with an increased emphasis on privacy and security [25], and the seamless integration of multimodal interaction (e.g., voice, touch, and gestures). As these technologies evolve (for example, Gaspar-Figueiredo et al. [23] used EEG to select adaptive graphical menus), AUIs will become more sophisticated, capable of providing highly adaptive, context-aware, and inclusive experiences. In conclusion, adaptive forms in graphical user interfaces represent a significant leap forward in user experience design provided that an appropriate mechanism for user-control is incorporated. By dynamically adjusting to the user's context, preferences, and behavior, these forms enhance usability, accessibility, and efficiency. As technology continues to advance, in particular, with the progress of machine learning, the potential for even more intelligent and intuitive adaptive forms will certainly grow, further transforming the landscape of form-based interaction.

## OPEN SCIENCE

SCALER is developed in Drupal V7.4, an open source Content Management System (CMS) which includes jQuery, along with its Drupal API 7.x and its Form API Reference (FAPI), with PHP as a general-purpose scripting language for web develop-ment. We release the SCALER source code on GitHub at https://github.com/jeanvdd/Scaler. A suite of five demonstration videos is also accessible on YouTube starting at https://youtu.be/1nPvrpZQTOo and ending at https://youtu.be/dJRDfqPO1Lc for the scoring function.

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