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PROBABILISTIC HUMAN-MACHINE COOPERATION IN PRODUCT PERSONALIZATION

Manfred Dangelmaier[1] [ORCID 0000-0001-9851-3055], Katharina Hölzle[2] [ORCID 0000-0002-9733-4650], Sabine Krieg[3], Ann-Kathrin Briem[4] [ORCID 0000-0002-5097-1898], Erwin Gross[5] [ORCID 0009-0007-8485-4415]

[1]Fraunhofer IAO, Fraunhofer Institute for Industrial Engineering IAO, Stuttgart, Germany
[2]University of Stuttgart, Institute of Human Factors and Technology Management (IAT), Stuttgart, Germany
[3]Fraunhofer IGB, Fraunhofer Institute for Interfacial Engineering and Biotechnology IGB, Stuttgart, Germany
[4]Fraunhofer IBP, Fraunhofer Institute for Building Physics IBP, Stuttgart, Germany
[5]Fraunhofer IPA, Fraunhofer Institute for Manufacturing Engineering and Automation IPA, Stuttgart, Germany

Abstract: *When personalizing products, AI algorithms relieve customers of the burden of choice. However, configuration recommendations by AI are probabilistic in nature. Users need to understand this to make well informed decisions.*
We therefore propose a user interaction paradigm for recommender and configuration systems which is based on Single Pass Bayesian Reasoning and on Suitability Probability Tables. Personalizing shoes is used as a use case for demonstration.
This interaction paradigm can be maintained even with modified algorithms. Generalizability to other classes of algorithms remains to be proven as well as correctness of interpretation by users and user acceptance.
Key Words: ***AI, Bayesian Reasoning, Recommender Systems, Human-machine Cooperation***

1. INTRODUCTION

The megatrend towards individualization does not stop at the market and its products. Mass customization or mass personalization provides the customer with a tailor-made product from mass production (Piller 2006; Bauernhansl et al. 2023). Product configurators are used for this purpose. With many configurable product features and characteristics, manual configuration by customers involves many decisions. For this reason, recommender systems employ user models and data to offer suitable product suggestions utilizing algorithms. This process is often probabilistic, as not all optimal characteristics can be represented deterministically as a function of the available user data. The algorithms recommend product features that are only likely to be suitable. This is one of the reasons why customers, as decision-makers, must be involved in the configuration process to a self-determined extent. This can range from making a purchase decision based on the algorithm's recommendation to completely manual configuration. At least, the Stuttgart model for personalized product creation follows this radically user-centric approach. This model (see Figure 1, Hämmerl & Dangelmaier 2018), which was developed at the Mass Personalization Performance Center (Held et al. 2018), has already been described several times and applied to various use cases. One use case discussed the integration of sustainability aspects into the personalization and configuration steps of the model. The model was enhanced to reflect the entire product life cycle and discussed the implications of each phase from a sustainability point of view. Furthermore, the applicability of the Stuttgart model to circular economy strategies was shown (Briem et al. 2022). However, the model has not yet defined how human-machine cooperation should be designed.

We are therefore looking for an algorithm for cooperative personalization that is understood by humans and can as well be executed by a probabilistic digital configurator or recommender.

2. INTERACTION WITH PROBABILISTIC ASSISTANCE SYSTEMS

Advances in the field of learning systems and artificial intelligence (AI) generally raise the question of how humans and machines will work together in the future. One answer that is currently being discussed for the future is: through natural language (Gross et al. 2020). Humans talk or chat with machines as they would with people.

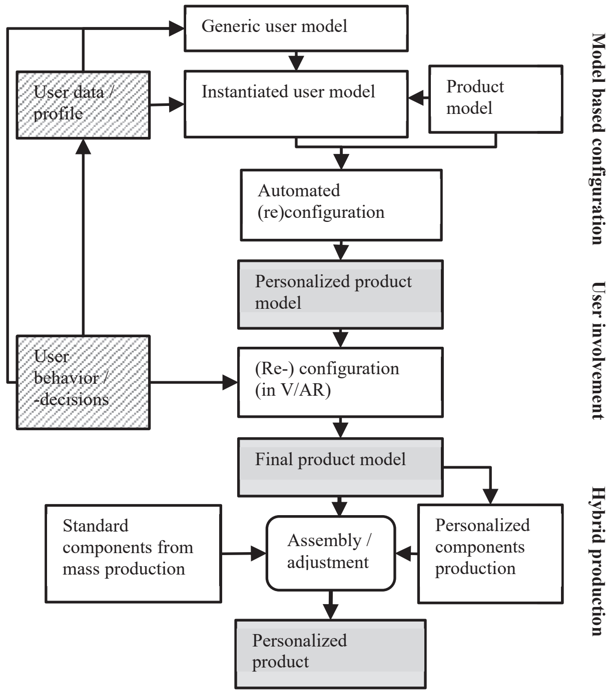

Fig. 1. *Stuttgart Model Mass Personalization*

Another answer based on the state of the art is: via a graphical user interface (GUI) that behaves through AI more dynamically and adaptively than before.

Neither modality generates an adequate mental model in humans about the probabilistic nature of the personalization problem nor of the (AI) algorithms. The reason is that talking in probabilities is avoided in natural speech. And modern GUIs tend to keep uncomfortable things like uncertainty invisible to the user. A natural language interaction promotes the mental model of a human counterpart. An adaptive GUI gives the impression of an unpredictable and arbitrary machine. Both are wrong. An appropriate model for many applications and in particular for the personalization in the Stuttgart model is that of the probabilistic decision assistant. A suitable mental model for such systems can be characterized as follows:

- Probabilistic assistance systems are subject to uncertainty.
- Their results are to be understood as recommendations.
- The users finally make decisions and bear responsibility for them.

For optimal decisions, the system must communicate the degree of uncertainty or risk to the human based on the data used. This is done by using a probabilistic language. If the machine indicates a probability of 90%, the users understand that they can only be 90% certain. If the chances of an alternative being suitable for the user are 10:3, then this is also associated with a certain degree of certainty or uncertainty. The interaction on the part of the machine must make clear that it is about probabilities or odds ratios and how high these are.

3. REQUIREMENTS FOR A COOPERATIVE CONFIGURATOR

The task of a recommender system is to utilize user data and user preferences available for a product system in order to find the best combination of features of a product for the user. In other words, we are looking for the product variant that is most likely to suit the user or is most likely to predict the purchase decision. We call such probabilities Preferabilities or, more understandably for users, Suitability Probabilities.

The configuration should be as efficient as possible. The algorithm should be suitable for humans and machines. It should be understandable and comprehensible for humans and be able to be executed by machines based on available data. It should take into account normative specifications in the sense of functional user requirements as well as subjective or collective user preferences. It should also provide data-based decision support and enable recommendations based on data from user profiles and previous user behavior.

4. USE CASE “SHOE”

We pick a simple fictitious yet realistic example to illustrate our approach and its application. A start-up comes up with the business idea of functionally personalized shoes. They want to provide an affordable and sustainable product that fits frequent special needs. They appreciate the philosophy of barefoot shoes with thin soles, keeping foot muscles active and thereby healthy. But they also understand a need for thick elastic and damping soles for people who have conditions or must walk on rigid surfaces in urban environments. Besides shoes size they provide shoes in different widths to adapt also to unusual foot geometries. Furthermore, they identified heel spur as well as the Haglund syndrome with Achilles bursitis as relevant to adapt for special needs. Both conditions show a prevalence of 10%. So, they will provide shoes with optional spur or haglund reliefs. Concerning design and aesthetics they feel that a small selection of occasion-related alternatives rather than gender specific ones would fit into today`s world.

This is a use case, which represents the class of products with independently configurable product features with discrete values. Our considerations will be applicable to any product from this class. We assume we have information about the users, in the sense of a user profile, which supports product selection. This information is somehow vague. So, we know that the client sometimes wears shoes of size 41 and sometimes 42. For some months a user might be plagued by Achilles bursitis and purchases shoes with Haglund relief. A few months later the condition has disappeared, and she returns to shoes without relief, and so on. So, a best guess of an automated configuration algorithm based on data available from the past can therefore only deliver results that are probably optimal. The user needs to understand this. In the Stuttgart model she corrects the decision of the algorithm and thereby provides data for the update of the user profile.

5. SINGLE PASS BAYESIAN REASONING AS AN IDEAL ALGORITHM

From the perspective of Bayesianism (Bovens et al. 2006; Bartelborth 2017) the Single Pass Bayesian Reasoning (SPBR) model is a suitable and understandable algorithm in this context. Bayesian reasoning uses Bayes’ theorem to calculate the probability of hypotheses based on evidence. In our case we have hypotheses about which product feature or which value of a product feature satisfies the client's needs best. With each piece of knowledge or evidence about the client we update our belief on the best feature value for the client. We do this by determining how much the piece of evidence strengthens the probability that a hypothesis is correct in relation to its alternative hypotheses. As an initial belief we can use e. g. uninformed priors like equal probabilities for the hypotheses or the frequency distributions of decisions of other clients. Next, we formulate this approach mathematically as an algorithm.

A set of collected user data **E** is to be mapped to values of a set of configurable product features **M** in order to decide on the most suitable values. We number the configurable features by index k. For the sake of clarity, we initially assume independent product features that are to be adapted to the users. In our case of a shoe purchase, these features are shoe size and width, shoe model, with or without heel spur or Haglund reliefs, and the cushioning properties of the sole. The various hypothetically optimal values per product feature are designated by the index j. The hypothetically possible values of M_k are named H_{kj}. We denote the relevant N_k information or data about the person with E_{ki}. The probabilities $P(H_{kj})$ that H_{kj} is the best value for the feature M_k for the user then result according to Bayes' theorem (Laplace 1814; Bayes & Price 1763) from Equation 1. This is Bayes' theorem repeatedly applied in in its ratio form.

$$\frac{P(H_{kj})}{P(\neg H_{kj})} = \frac{P(H_{kj})}{1 - P(H_{kj})} = \prod_{i=0}^{N_k} \frac{P(E_{ki}|H_{kj})}{P(E_{ki}|\neg H_{kj})} \quad (1)$$

The prerequisite for the validity of the formula from an epistemological point of view is that the user data E_{ik} for all i are not mutually dependent. In addition, it is assumed that for each product feature exactly one value H_{kj} must be chosen to define a product, i.e. the H_{kj} are mutually exclusive.

The $P(E_{ki}|H_{kj})$ and $P(E_{ki}|\neg H_{kj})$ are called likelihoods. Their quotients are called Bayes Factors. The Bayes Factor indicates how much the information E_{ki} about the users strengthens the suitability probability of the characteristic H_{kj} compared to its alternatives. The product of all N_k Bayes Factors yields the Suitability Probability of the j^{th} value in relation to all other values.

The recommender system will then recommend the value with the maximum Suitability Probability:

$$\mathrm{P}(\mathrm{H}_k) = max(P(H_{kj})) \quad (2)$$

Where do the likelihoods $P(E_{ki}|H_{kj})$ or Bayes factors come from? There are several possibilities. The most important are

1. *Direct and subjective assessment of suitability probabilities by customers*: This is the case when a customer directly states a 3:2 preference for shoe model Berlin and shoe model Paris.
2. *Parameterized likelihood functions*: Such functions map, for example, the parameters foot length and foot width to shoe size and shoe width. These are functional and normative requirements that are formulated by the customer or are measured against the customer. It is possible to formulate deterministic parametric requirements by setting the likelihood of a value to 1 and of the other values to 0.
3. *Likelihoods as frequencies from a database*: If you know that women prefer the alternative shoe designs in a certain ratio, you can use this likelihood ratio as Bayes Factor for the feature Model. You can also use a customer's shopping history as a personalized data source.

The advantage of the Bayesian approach is that it handles subjective preferences and parameter-based requirements as well as data-based probabilities in the same equation. This makes it universally applicable to advisory and decision support situations (Dangelmaier et al. 2022; Dangelmaier & Hölzle 2023).

6. USER-FRIENDLY LANGUAGE AND INTERACTION

The above formulas describe the ideal algorithm exactly. However, it is neither necessary nor desirable for users to know them. To make an informed decision, however, they do need to know the Suitability Probabilities of all of the features. Only then can they interpret the proposal of the algorithm correctly and make an adequately informed decision. Table 1 gives an example of a Suitability Probability Table (SPT). The cut-out shows 6 configurable product features and 18 potential values. If we extend the range of the size feature to 13 values and the width feature to 7 values, we will have 30 values which results in 2912 product variants in total for our use case. Empty P cells in Table 1 are to be interpreted as 0. 128 combinations seem to be more or less suitable for the user. Two variants "Berlin, size EU 40, width H, thin sole, without Haglund heel relief, either with or without heel spur relief" are, according to Equation 2, recommended to the user and are printed in bold in the Table. Let us furthermore assume that the user made the decisions highlighted in gray.

Table 1. *Example of a probabilistic shoe configuration using suitability probabilities P.*

Model P	**Berlin** **0.4**	Paris 0.3	Lhasa 0.2	Hawaii 0.1
Size P	...39	**40** **0.8**	41 0.2	42...
Width P	F	G	H **0.8**	J... 0.2
Sole P	**Thin** **0.7**		Elastic 0.3	
Haglund relief P	Yes 0.1		**No** **0.9**	
Spur relief P	**Yes** **0.5**		**No** **0.5**	

We see the advantage of the recommender. The decision load is reduced from 2912 to 128 variants by excluding options (P=0). Two equally suitable variants are recommended. If the user had followed the suggestion, he would only have had to decide whether he wanted heel spur relief. Let us now assume the user deviates from the suggestion. He opts for the more elegant model Paris. This is justified because he wants to wear it for more formal occasions. The algorithm should not intervene in this case. In favor of a visually slimmer foot, he chooses shoe width G with shoe size 41 instead of H with 40, contrary to the recommendation. According to Table 2, this seems irrational and implies negative consequences for foot health. The algorithm should warn the user, accordingly, taking in account the background knowledge, that feet tend to grow rather than to shrink. On the other hand, a Hallux operation could, however, justify the deviating width selection. The user knows and can decide.

Table 2. *Potentially irrational user decisions - marked in black*

Model P	**Berlin** **0.4**	Paris 0.3	Lhasa 0.2	Hawaii 0.1
Size P	...39	**40** **0.8**	41 0.2	42...
Width P	F	G	H **0.8**	J... 0.2
Sole P	**Thin** **0.7**		Elastic 0.3	
Haglund relief P	Yes 0.1		**No** **0.9**	
Spur relief P	**Yes** **0.5**		**No** **0.5**	

In case the user finally orders, his decisions will be stored in the user database of the company and will in future contribute to the recommendations of the algorithm. This is a simple version of a learning system and of the feedback of user decisions to a learning system as shown in Figure 1.

We will now show how a dependent feature like Sustainability can be added. The idea is to provide the user with feedback how sustainable their choices are. In our example the features Model and Sole differ in environmental impacts. It is not useful to disclose differences in environmental impacts of shoe size or width to the user because it is not desirable to encourage them to buy unhealthy shoes for the sake of ecology, e. g. by saving material due to choosing a smaller size. This approach is in accordance with the internationally standardized and widely adopted LCA methodology which is built around the so-called functional unit. It makes sure that the function of a product must be fulfilled when comparing different product variants.

We mark the environmental benefit per value with stars. More stars mean a more environmentally friendly product. We add the achieved stars and present them in the Eco line at the bottom of Table 3. The P value there means the proportion of stars relative to the achievable maximum. This is a relative performance measure and not a probability like before. But the terms Preferability or Suitability also cover such characteristics if they fall in the range between 0 and 1, and 1 stands for the most desirable value, and each star stands for the same environmental benefit.

We see in Table 3 that the user followed the recommendation of the algorithm and selected healthy size and width parameters now. The environmental benefit is close to the best possible value, meaning low impact for the environment compared to other options. The user was originally nudged to switch to the more sustainable Model "Lhasa" with three stars. Finally, he did not do so because the Model is too informal for his purposes. Again, the user knows more and decides.

Table 3. *Probabilistic shoe configuration with dependent sustainability feature – sustainability marked by stars*

Model P	**Berlin** **0.4 ***	Paris 0.3 **	Lhasa 0.2 ***	Hawaii 0.1 *
Size P	...39	**40** **0.8**	41 0.2	42...
Width P	F	G	H **0.8**	J... 0.2
Sole P	**Thin** **0.7 *****		Elastic 0.3*	
Haglund relief P	Yes 0.1		**No** **0.9**	
Spur relief P	**Yes** **0.5**		**No** **0.5**	
Eco P	***** **0.83**			

7. DISCUSSION

While we presented a simple recommender algorithm, assumingly the most elementary one based on Bayesian principles, we did not formulate a full design. We just gave enough information to describe the human-machine-interaction with probabilistic recommenders.

Considering probabilistic communication changed the interaction paradigm of the Stuttgart Model. While the naïve initial idea was to propose an optimal solution in Virtual Reality and then let the user adjust the options like in a manual configurator, we ended up with a probabilistic interaction paradigm with Suitability Probability Tables, which provide a reasonably reduced amount of data in a human readable form. Such an interface empowers the users and makes them responsible of informed decisions.

This SPBR algorithm fulfills all the requirements set out in Chapter 3 by design. It does not only fit the use case but all configuration tasks with finitely countable options and independent evidence about the customer and independent features as well as dependent decision criteria. In practice, however, complications such as incompatible values or dependent features occur. For example, the model Paris may not be manufactured with an elastic sole. Or, in the case of complaints due to a heel spur, the preferences change considerably for a few months. This could be taken into account by a time-dependent model. For such reasons algorithms in practice will deviate from the simple model we formulated above.

The sustainability example we showed was a simplified first approach to this overall complex topic. Improving various dimensions of sustainability aspects is a complex optimization problem. In the given example we assume that a single-point indicator was defined to communicate these aspects to the user. The user is nudged to select a combination with higher environmental impact. Consequently, the responsibility of minimizing these impacts is laid upon the user. This burden of being responsible for his or her choice regarding the environmental impacts could be kept small, if the algorithm ensures that a specified sustainability threshold is upheld. In the future, algorithms will have to address this issue of aligning user preference and sustainability optimum.

However, these complications not invalidate the probabilistic interaction paradigm we used. It remains recommendable from the perspective of informed probabilistic decisions as long as the concept can be mapped by linear Preferability measures between 0 and 1. We have shown in the case of dependent performance features like the environmental benefit how the Preferability paradigm can be maintained.

On the one hand, further work should investigate additional use cases and verify the claimed applicability of probabilistic interaction for other classes of recommender algorithms. On the other hand, it remains to be empirically clarified, how users cope with probabilistic communication. Our mathematical and normative considerations have not yet proven that it is appropriately interpreted and accepted by customers.

Therefore, we recommend considering probabilistic interaction with SPT in recommender and configuration systems. But usability and acceptance studies are needed to verify their benefits.

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CORRESPONDENCE

Dr.-Ing. Manfred Dangelmaier
Fraunhofer IAO
Nobelstraße 12
70569 Stuttgart, Deutschland
manfred.dangelmaier@iao.fraunhofer.de

Prof. Katharina Hölzle
Fraunhofer IAO
Nobelstraße 12
70569 Stuttgart, Deutschland
katharina.hoelzle@iao.fraunhofer.de

Ann-Kathrin Briem
Fraunhofer IBP
Nobelstraße 12
70569 Stuttgart, Deutschland
ann-kathrin.briem@ibp.fraunhofer.de

Sabine Krieg
Fraunhofer IGB
Nobelstraße 12
70569 Stuttgart, Deutschland
sabine.krieg@igb.fraunhofer.de

Dr.-Ing. Erwin Gross
Fraunhofer IPA
Nobelstraße 12
70569 Stuttgart, Deutschland
erwin.gross@ipa.fraunhofer.de