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Automated Detection of Decision-Making Style, Based on Users' Online Mouse Pointer Activity

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Abstract: *Decision-making* (*DM*) and online activity go hand in hand in many domains of everyday life (e.g., consumer behaviour, financial and investment choices, career development, health and psychological well-being). DM style refers to consistent behavioural patterns in the way different individuals approach DM situations. In this study, we explored the feasibility of inferring DM style from the trace of mouse cursor (or pointer) activity that users generated while performing an online task (the task required no explicit DM). We focussed on maximizing and satisficing DM style. Based on a set of spatial, temporal and spatial-temporal features that were extracted from mouse activity data and on measures of DM style assessed with a conventional self-report questionnaire, we modelled DM style in a supervised machine learning approach. The results show that the models of DM style have between good and high predictive accuracy. Guided by these results, we propose that this mouse-based method might play a useful role in computational recognition of DM style and merits further development. Future work will test the ability of pointer-based models to meaningfully link psychological measures of DM style to objective measures and outcomes of real-world DM situations.

1 INTRODUCTION

Decision-making (*DM*) style refers to consistent patterns of behaviour in the way individuals approach DM situations (Scott & Bruce, 2016). For example, maximizers tend to approach DM situations by expending a lot of effort in searching and processing the choice alternatives in order to determine the *best* choice (i.e., maximizing style). In contrast, satisficers tend to search and process the choice alternatives in order to determine the choice that is *good enough* (i.e., satisficing style) (Schwartz, 2000).

Maximizing and satisficing style are considered by some researchers as habit-based tendencies to react in a certain way to specific DM situations (e.g., a particular DM style when choosing an item from a range of consumer goods on the internet but not in the local grocery store) (Scott & Bruce, 2016). Instead, recent data shows that maximizing and satisficing tendencies may be general to DM situations across different DM domains (i.e., consumer goods, health and life decisions, finance) (Moyano-Diaz & Mendoza-Llanos, 2021). Irrespective of whether DM style is a situation-specific habit or a general disposition (or trait) of personality (Thunholm, 2004), and given that DM and online activity are inextricably linked in many DM domains (Kokkoris, 2018), we asked if maximizing and satisficing style can be inferred from the unique trace of online activity generated while users interact with digital technology.

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Much of the work of developing the maximizing and satisficing concepts and their various components (e.g., experienced decision difficulty) has focussed on their assessment (Cheek & Schwartz, 2016). The main method of assessing DM style is the traditional paper-and-pencil self-report questionnaire (Boyle, 2009). A drawback of this method is that it is impracticable for assessing online users and unscalable to the many different online DM situations and domains. Depending on the area of application, online DM style might be better served using an automated procedure with the potential for near real-time processing.

Research in *computational personality recognition* (*CPR*) and biometrics shows that the digital trace of a user's hand-held computer mouse can be used to automatically assess user personality and identity (Ahmed, Awad, & Traore, 2007; Meidenbauer, Niu, Choe, Stier, & Berman, 2022; Zhao, Miao, & Cai, 2022). Recent work shows also that DM style can be inferred from various data sources, such as bodily and facial behaviour (Connors, Rende, & Colton, 2013; Guo, Liu, Wang, Zhu, & Zhan, 2022). However, it is not clear whether and how well the activity of a mouse cursor, or pointer, could be used for predictive modelling of maximizing and satisficing style.

Numerous features can be extracted from the movements and clicks of the pointer activity (Cepeda, Dias, Rindlisbacher, Gamboa, & Cheetham, 2021; Cepeda et al., 2018; Gamboa & Fred, 2003). These include temporal features (e.g., acceleration), spatial features (e.g., curvature of trajectory) and composite features based on complex spatial-temporal mouse movements (e.g., hovering patterns) (Cepeda et al., 2021).

We explored the feasibility of using pointer activity data to predict users' maximizing and satisficing style. To this end, we acquired mouse activity data while users performed an online task and automatically extracted a broad set of temporal, spatial and composite features (Cepeda et al., 2021). The DM style of users was measured by self-report questionnaire (Turner, Rim, Betz, & Nygren, 2016). We then modelled the feature and style data in a supervised machine learning approach.

The resulting predictive models of DM style demonstrated between good and high accuracy. Guided by these initial models, we suggest that further development of this pointer-based method might contribute to computational recognition of DM style. We consider the potential application of this method and future work to develop it further.

2 METHODOLOGY

2.1 Participants

N=79 (mean age=23.8, SD=4.07; 58 female) healthy individuals, native speakers of Standard German, with normal or corrected-to-normal vision and no reported neurological or psychiatric illness participated. Each participant gave written informed consent and received 20 Swiss Francs (or course credits if a student) for participation. The local Ethics Committee waived the study (KEK Nr.: 2022-00713).

2.2 Dataset

Pointer features were extracted from data acquired while participants engaged in the online task of completing a digital German-language version of the 34-item Maximising Inventory (MI) (Turner et al., 2016). The MI has three scales: decision difficulty, alternative search, and satisficing, the first two of which capture two different components of maximizing behaviour. Participants rated each item, using a 5-point Likert-type scale (1= "strongly disagree" to 5= "strongly agree"). Cronbach's alpha for each scale was 0.71, 0.87, 0.73, respectively (comparable to the original English version).

2.3 Procedure

All participants were tested individually in a small, quiet and dimly lit experimental room. The experiment lasted approximately 60 min. First, informed consent and demographic data was collected. Then a 1 min. resting baseline was performed at the beginning of the experiment to facilitate laboratory adaptation. The questionnaire was administered using LimeSurvey, an open-source survey web app (LimeSurvey). After completion of the survey, participants were informed that all data, including mouse data, would be analysed and that they could withdraw their data from the study if they wished without stating a reason for doing so.

2.4 Data Acquisition

A web browser extension acquired the mouse activity (Cepeda et al., 2019). The data included the (x,y) coordinates of mouse position in pixels, the questionnaire item and mouse events (click or no click) associated with each mouse position, timestamp (ms.), and click duration (ms. between button press and release). Data were stored in the MongoDB database (MongoDB) before exporting for pre-processing. Features were extracted from the mouse data and checking data consistency (within and across participant data), data merging and checking for missing data followed an automated procedure (Cepeda et al., 2021).

2.5 Data Analyses

We used non-linear Random Forest (RF) regression (Ho, 1998), with 108 temporal, spatial and composite features as independent variables and the scores of each scales as dependent variables.

Model input data was normalized (Gopal Krisna Patro & Sahu, 2015). We set the number of decision trees to 1000 and ran the bagging procedure 100 times. A 50% train-test split procedure was applied (i.e., a conservative approach to avoid overfitting) (Kuhn & Kjell, 2018). RF performance is relatively robust against parameter specifications (Probst, Bischl, & Boulesteix, 2019). The train-test procedure selects features that optimize model accuracy and resist non-informative predictors (Kuhn & Kjell, 2018). The bagging procedure is used for training decision trees (Efron, 1994). The individual bootstrap trees were aggregated to compute a final prediction of performance for each model (Hastie, 2009; Ho, 1998; James, 2013). Using the bagging procedure, RF achieves higher, more stable predictive accuracy with limited risk of overfitting (Valizadeh, Hanggi, Merillat, & Jancke, 2017; Valizadeh, Riener, & Jancke, 2019).

We used Mean Absolute Percentage Error (MAPE) (i.e., difference between the actual value and predicted value divided by actual value) for model evaluation. As a percentage value, MAPE simplifies comparison of performance across models. To present results, we converted MAPE by computing 100-MAPE so that higher values indicate better performance (Kleinbaum, Kupper, Muller, & Nizam, 1998).

First, we computed prediction models for each scale using all features in each model. Second, we computed 12 models, one for each combination of scale and feature type (temporal, spatial, composite, as well as all features together). Third, we performed Welch's ANOVA (Delacre, Leys, Mora, & Lakens, 2019; Welch, 1938), with scale (3 levels; decision difficulty, alternative search, satisficing) and feature type (4 levels; temporal, spatial, composite, all features) as independent factors, and MAPE as dependent variable. We tested for differences in model accuracy between the scales and between the types of features. The alpha threshold was set to .001

We used Scikit toolbox in Python for RF testing and training (Pedregosa et al.) and R Version 4.0.2 for analyses (Welch's ANOVA) and creating figures (R-Core-Team, 2022).

3 RESULTS

The mean scores of the scales were M=2.96 (SD=0.53) for decision difficulty, M=3.56 (SD=0.70) for alternative search, M=3.45 (SD=0.45) for satisficing.

The prediction models for the scales, with all features in each model, show accuracies of 81% for alternative search, 85% for decision difficulty and 88% for satisficing (see Fig. 1 and Table 1).

Table 1: Summary of the prediction models for each combination of feature type and scale.

Feature type	**Scale**		
	Alternative search (%)	Decision difficulty (%)	Satisficing (%)
All features	0.81	0.85	0.88
Composite	0.82	0.84	0.88
Spatial	0.82	0.85	0.89
Temporal	0.82	0.84	0.88

Note: % indicates MAPE after transforming this by 100-MAPE so that a higher value corresponds to smaller prediction error.

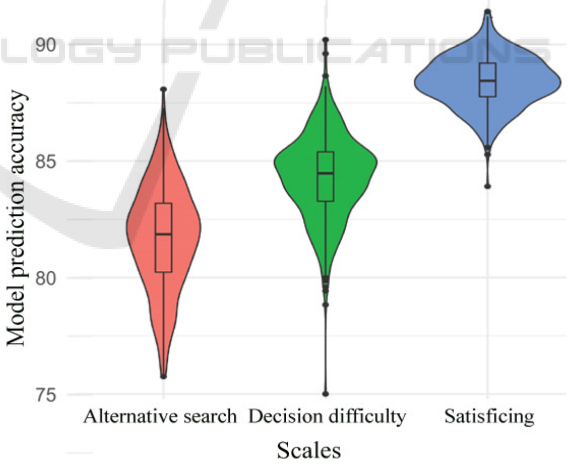

Figure 1: Violin plots showing the median, variability and probability density of prediction models for the decision difficulty, alternative search and satisficing scales. All the features were used as input in each model.

The F-Welch tests showed a significant difference in model accuracy between these scales, $F_{(2,779.35)} = 1164.82$, $p < .001$., and that model performance accuracy was not significantly different between feature types, $F_{(3,\ 663.18)}=1.17$, $p=0.32$ (see Fig. 2 and 3).

Overall, the results suggest between good and high performance of all prediction models (i.e., a low degree of error between the predicted and actual values (see Table 1).

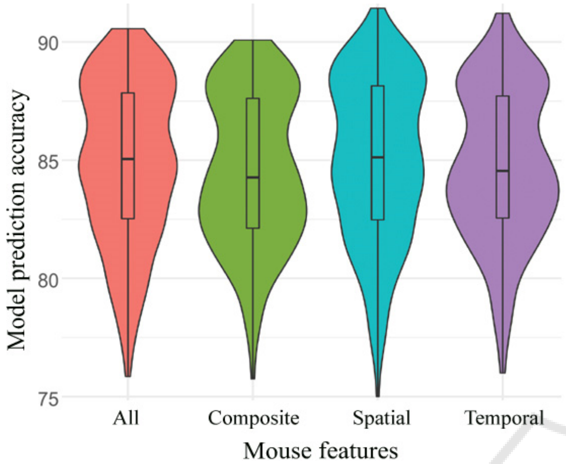

Figure 2: Violin plots showing the distributional characteristics of the prediction models for each type of feature and all features together (x-axis) against model accuracy (y-axis).

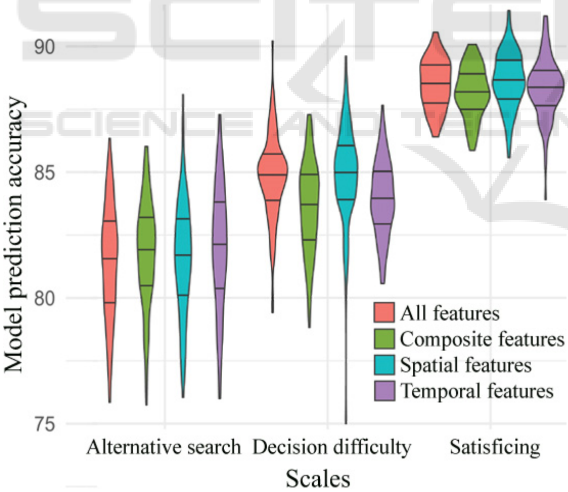

Figure 3: Grouped violin plots showing the distributional characteristics of the prediction models for each combination of scale and feature (x-axis) against prediction accuracy (y-axis).

4 CONCLUSIONS

In this paper, we propose the use of a pointer-based method for automatically inferring the DM style of users from the digital trace of their online activity. As a proof of concept, we focussed on the psychological constructs of maximising and satisficing, as we considered these relevant for DM in various domains (e.g., consumer behaviour, financial and investment choices); other DM styles that could be investigated (Cosenza & Ciccarelli, 2019; Harren, 1979; Janis & Mann, 1977; Leykin, 2010; Saled, 2017; Weerasekara & Bhanugopan, 2022). We examined three particular scales of maximising and satisficing, but other scales could be considered (Cheek & Schwartz, 2016).

All the models showed good predictive accuracy, with the decision difficulty and satisficing scales nearing high performance (Lewis, 1982). There was a significant difference in model accuracy between the scales but not between the three types of features used for modelling. Overall, these initial findings speak in favour of developing and testing this method further.

As an initial proof-of-concept study, we did not examine whether there is any decay in model performance when porting these models to other unrelated online tasks. For this, we note that the online task did not require any explicit form of DM (though it did require reporting of behaviour related to DM situations). A further analysis indicated good stability of all models, suggesting that our sample size is adequate for this proof-of-concept study.

This mouse-based (or pointer-based) method has advantages over traditional self-report methods. Remote pointer-based data collection is low cost, easy to implement, nonintrusive (i.e., does not interrupt the natural flow of user activity) and easily scaled up. It can deliver results in near real-time and could be re-applied to touch screen data.

Future work will seek to understand the impact on model performance of factors that influence users' pointer activity, such as technical factors (e.g., different mouse devices), environmental factors (e.g., ambient noise), task-related factors (e.g., nature and goal of the online task) and individual human factors (e.g., age). This could pave the way to developing more robust models, though careful consideration must be given to the choice of DM style (or related constructs) (Misuraca, 2018) and the psychometric properties of the self-report measures of DM style. This pointer-based method could also contribute to developing a better understanding of whether DM style is a habitual tendency that is specific only to certain situations or a more general pattern of behaviour across time and situations (i.e., a personality trait). Whether a habit or trait, the ability of models based on a pointer device (e.g., computer mouse, trackpad or digital pen) to meaningfully link psychological measures of DM style to objective measures of real-world DM needs to be evaluated.

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REFERENCES

Ahmed, A., Awad, E., &, & Traore, I. (2007). A New Biometric Technology Based on Mouse Dynamics. *IEEE Transactions on Dependable and Secure Computing, 4*(3), 165-179. doi:10.1109/tdsc.2007.70207

Boyle, G., & Helmes, E. (2009). Methods of personality assessment. In *The Cambridge handbook of personality psychology* (126 ed., Vol. 110, pp. 110-126): Cambridge University Press.

Cepeda, C., Dias, M. C., Rindlisbacher, D., Gamboa, H., & Cheetham, M. (2021). Knowledge extraction from pointer movements and its application to detect uncertainty. *Heliyon, 7*(1), e05873. doi:10.1016/j.heliyon.2020.e05873

Cepeda, C., Rodrigues, J., Dias, M. C., Oliveira, D., Rindlisbacher, D., Cheetham, M., & Gamboa, H. (2018). Mouse Tracking Measures and Movement Patterns with Application for Online Surveys. In *CD-MAKE 2018: Machine Learning and Knowledge Extraction* (pp. 28-42).

Cepeda, C., Tonet, R., Osorio, D., Noronha, S., Hugo, P., Cheetham, M., & Gamboa, H. (2019). Latent: A Flexible Data Collection Tool to Research Human Behavior in the Context of Web Navigation. *IEEE Access, 7*, 77659-77673. doi:10.1109/access.2019.2916996

Cheek, N. N., & Schwartz, B. (2016). On the meaning and measurement of maximization. *Judg. Decis. Mak.* (11), 126–146.

Connors, B. L., Rende, R., &, & Colton, T. J. (2013). Predicting individual differences in decision-making process from signature movement styles: an illustrative study of leaders. *Front Psychol, 4*, 658. doi:10.3389/fpsyg.2013.00658

Cosenza, M., & Ciccarelli, M., & Nigro, G. (2019). Decision-Making Styles, Negative Affectivity, and Cognitive Distortions in Adolescent Gambling. *J Gambl Stud, 35*(2), 517-531. doi:10.1007/s10899-018-9790-y

Delacre, M., Leys, C., Mora, Y. L., & Lakens, D. (2019). Taking Parametric Assumptions Seriously: Arguments for the Use of Welch's F-test instead of the Classical F-test in One-Way ANOVA. *International Review of Social Psychology, 32*(1). doi:10.5334/irsp.198

Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. New York: Chapman and Hall/CRC.

Gamboa, H., & Fred, A. (2003). *An Identity Authentication System Based On Human Computer Interaction Behaviour.* Paper presented at the PRIS.

Gopal Krisna Patro, S., & , & Sahu, K. K. (2015). Normalization: A Preprocessing Stage. *IARJSET* (10.17148/IARJSET).

Guo, Y., Liu, X., Wang, X., Zhu, T., & Zhan, W. (2022). Automatic Decision-Making Style Recognition Method Using Kinect Technology. *Front Psychol, 13*, 751914. doi:10.3389/fpsyg.2022.751914

Harren, V. A. (1979). A model of career decision making for college students. *Journal of Vocational Behavior*(14), 119–133.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2 ed.): Springer-Verlag.

Ho, T. K. (1998). The Random Subspace Method for Constructing Decision Forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 8*(20), 832–844. doi:doi:10.1109/34.709601.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*: Springer-Verlag.

Janis, I. L., & , & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice and commitment*. New York: The Free Press.

Kleinbaum, D., Kupper, L., Muller, K., & Nizam, A. (1998). *Applied Regression Analysis and Multivariable Methods*. Pacific Grove, CA: Duxbury.

Kokkoris, M. D. (2018). Maximizing Without Borders: Evidence That Maximizing Transcends Decision Domains. *Front Psychol, 9*, 2664. doi:10.3389/fpsyg.2018.02664

Kuhn, M., &, & Kjell, J. (2018). *Applied Predictive Modeling*. New York, NY: Springer.

Lewis, C. D. (1982). *Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting*. London; Boston: Butterworth Scientific.

Leykin, Y., & DeRubeis, R. J. (2010). Decision-making styles and depressive symptomatology Development of the Decision Styles Questionnaire. *Judgment and Decision Making, 5*(7), 506–515.

LimeSurvey. LimeSurvey: An Open Source survey tool Retrieved from http://www.limesurvey.org

Meidenbauer, K. L., Niu, T., Choe, K. W., Stier, A. J., & Berman, M. G. (2022). Mouse movements reflect personality traits and task attentiveness in online experiments. *J Pers*. doi:10.1111/jopy.12736

Misuraca, R., & Fasolo, B. (2018). Maximizing versus satisficing in the digital age: Disjoint scales and the case for "construct consensus. *Personality and Individual Differences,* (121), 152-160.

MongoDB. MongoDB 5.0 Documentation. Retrieved from https://docs.mongodb.com/

Moyano-Diaz, E., & Mendoza-Llanos, R. (2021). Yes! Maximizers Maximize Almost Everything: The Decision-Making Style Is Consistent in Different Decision Domains. *Front Psychol, 12*, 663064. doi:10.3389/fpsyg.2021.663064

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., , Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R.,, Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., , . . . Duchesnay, E. Scikit-learn: Machine learning in Python. *The Journal of Machine Learning Research, 12*, 2825-2830. Retrieved from https://scikit-learn.org/

Probst, P., Bischl, B., & Boulesteix, A.-L. (2019). Tunability Importance of hyperparameters of machine learning algorithms. *The Journal of Machine Learning Research, 20*(1), 1934–1965.

R-Core-Team. (2022). R: A language and environment for statistical computing. Retrieved from https://www.R-project.org/.

Saled, M., Alhosseini, S. E., & Slambolchi, A. (2017). A Review of Consumer Decision-Making Styles: Existing Styles and Proposed Additional Styles. (07), 33-44.

Schwartz, B. (2000). The tyranny of freedom. *American Psychologist, 55*, 79-88.

Scott, S. G., & Bruce, R. A. (2016). Decision-Making Style: The Development and Assessment of a New Measure. *Educational and Psychological Measurement, 55*(5), 818-831. doi:10.1177/0013164495055005017

Thunholm, P. (2004). Decision-making style: habit, style or both? *Personality and Individual Differences, 36*(4), 931-944. doi:10.1016/s0191-8869(03)00162-4

Turner, B. M., Rim, H. B., Betz, N. E., & Nygren, T. E. (2016). The maximization inventory. *Judgment and Decision Making, 7*(1), 48-60. doi:10.1037/t45865-000

Valizadeh, S. A., Hanggi, J., Merillat, S., & Jancke, L. (2017). Age prediction on the basis of brain anatomical measures. *Hum Brain Mapp, 38*(2), 997-1008. doi:10.1002/hbm.23434

Valizadeh, S. A., Riener, R., Elmer, S., & Jancke, L. (2019). Decrypting the electrophysiological individuality of the human brain: Identification of individuals based on resting-state EEG activity. *Neuroimage, 197*, 470-481. doi:10.1016/j.neuroimage.2019.04.005

Weerasekara, S., & Bhanugopan, R. (2022). The impact of entrepreneurs' decision-making style on SMEs' financial performance. *Journal of Entrepreneurship in Emerging Economies*. doi:10.1108/jeee-03-2021-0099

Welch, B. L. (1938). The significance of the difference between two means when the population variances are unequal. *Biometrika, 29*, 350–362.

Zhao, Y., Miao, D., & Cai, Z. (2022). Reading Personality Preferences From Motion Patterns in Computer Mouse Operations. *IEEE Transactions on Affective Computing, 13*(3), 1619-1636. doi:10.1109/taffc.2020.3023296.