Einführung in die Forschungsmethoden der Psychologie

BSc Philosophie-Neurowissenschaften-Kognition WiSe 23/24

BSc Psychologie WiSe 23/24

Prof. Dr. Dirk Ostwald

(2) Psychologische Forschung

Einführung

Beispiele grundlagenorientierter psychologischer Forschung

Beispiele anwendungsorientierter psychologischer Forschung

Selbstkontrollfragen

Einführung

Beispiele grundlagenorientierter psychologischer Forschung

Beispiele anwendungsorientierter psychologischer Forschung

Selbstkontrollfragen

Psychologie

Wissenschaft des menschlichen Erlebens, Verhaltens und Handelns

Beschreiben
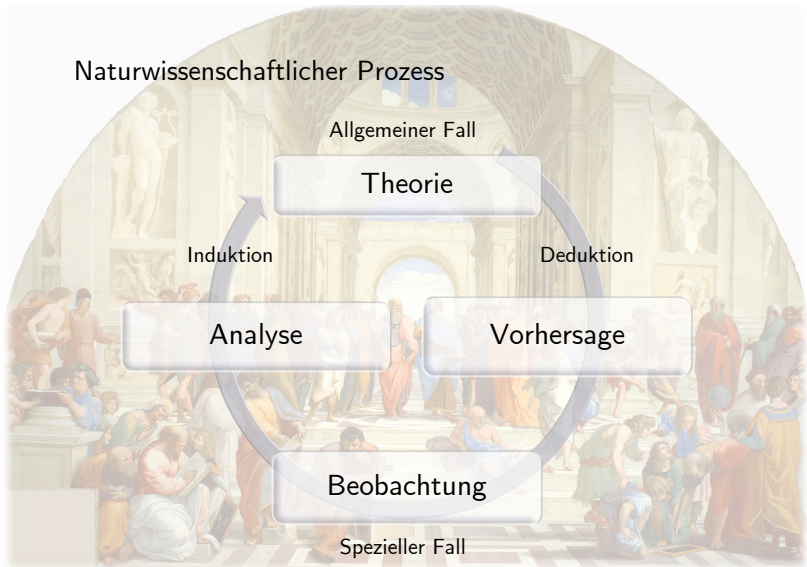➤ Benennen und Klassifizieren neuropsychologischer Phänomene

Erklären
➤ Entwicklung mechanistischer neuropsychologischer Modelle
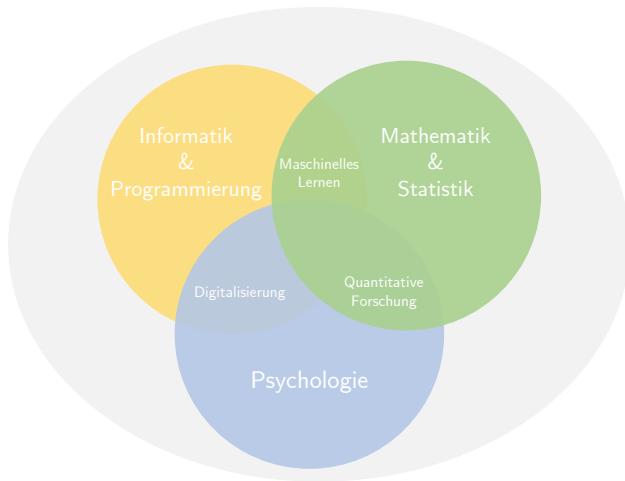
Vorhersagen
➤ Prognose zukünftigen Erlebens, Verhaltens und Handelns

Verändern
➤ Prävention, Diagnose, Behandlung psychiatrischer Erkrankungen

Naturwissenschaftlicher Prozess

Allgemeiner Fall

Theorie

Induktion

Deduktion

Analyse

Vorhersage

Beobachtung

Spezieller Fall

Psychologische Datenwissenschaft

Grundlagenforschung

- Verstehen der mechanistischen Zusammenhänge eines Gegenstandbereichs.

- Verstehen, wie und warum etwas funktioniert, wie es funktioniert.

- Wissensbasierte intuitive Generation neuer mechanistischer Ideen.

- Quantitative Überprüfung der generierten Ideen im empirischen Kontext.

- Kommunikation und rationale Diskussion der Ideen und ihres empirischen Supports.

Anwendungsforschung

- Verstehen, welche Form von Intervention ein gewünschtes Ergebnis hervorbringt.

- Verstehen, wie etwas verändert werden kann ohne notwendig, zu verstehen, wie es funktioniert.

- Wissensbasierte intuitive Generation neuer Interventionsformen.

- Quantitative Überprüfung von Interventionen im empirischen Kontext.

- Kommunikation und rationale Diskussion der Interventionen und ihres empirischen Supports.

Einführung

Beispiele grundlagenorientierter psychologischer Forschung

Beispiele anwendungsorientierter psychologischer Forschung

Selbstkontrollfragen

Human Belief State-Based Exploration and Exploitation in an Information-Selective Symmetric Reversal Bandit Task

Lilla Horvath[1] · Stanley Colcombe[2] · Michael Milham[2] · Shruti Ray[3] · Philipp Schwartenbeck[4] · Dirk Ostwald[5,6]

Abstract

Humans often face sequential decision-making problems, in which information about the environmental reward structure is detached from rewards for a subset of actions. In the current exploratory study, we introduce an information-selective symmetric reversal bandit task to model such situations and obtained choice data on this task from 24 participants. To arbitrate between different decision-making strategies that participants may use on this task, we developed a set of probabilistic agent-based behavioral models, including exploitative and explorative Bayesian agents, as well as heuristic control agents. Upon validating the model and parameter recovery properties of our model set and summarizing the participants' choice data in a descriptive way, we used a maximum likelihood approach to evaluate the participants' choice data from the perspective of our model set. In brief, we provide quantitative evidence that participants employ a belief state-based hybrid explorative-exploitative strategy on the information-selective symmetric reversal bandit task, lending further support to the finding that humans are guided by their subjective uncertainty when solving exploration-exploitation dilemmas.

Keywords Bandit problem · Agent-based behavioral modeling · Exploration · Exploitation

Horvath et al. (2021)

Gegenstandsbereich und Phänomen

Menschen müssen oft Entscheidungen unter Unsicherheit treffen

Menschen müssen manchmal informations- und gewinnbringende Handlungen abwägen

Übertragungsrate ↓

Eigener Status?

Übetragungsrate ↑

Eigener Status ✓

- Wie gehen Menschen dabei vor?

- Wie lernen Menschen in solchen Situationen Entscheidungen zu treffen?
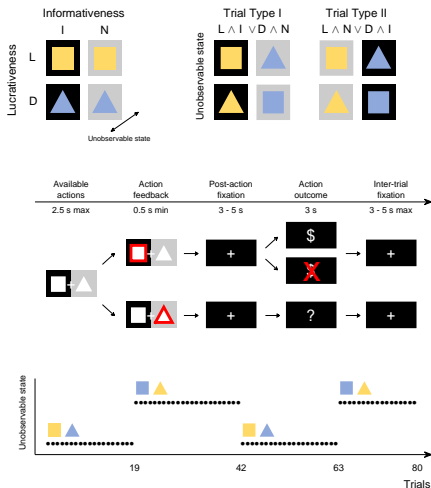
Horvath et al. (2021)

Experimentelle Simulation

Verhaltensdatenaufnahme

Horvath et al. (2021)

Experimentelle Simulation

Horvath et al. (2021)

Theorie

Künstliche Intelligenz - Artificial Agent

$$\mathsf{M}_{\mathsf{Agent}} := (S, A, R, O, p(s_1^1), p(s_{t+1}^1|s_t^1), p^{a_t}(o_t|s_t^1), p^{a_t}(r_t|s_t^1), v, d)$$

- Dynamisches handlungsabhängiges generatives Modell

$$p^{a_{1:T}}(s_{1:T}^1, o_{1:T}) = p(s_1^1) \prod_{t=1}^{T} p^{a_t}(o_t|s_t^1) p(s_{t+1}^1|s_t^1)$$

- Handlungsabhängige Zustandsschätzung (Belief State)

$$p^{a_{1:t-1}}(s_t^1|o_{1:t-1}) = \frac{\sum_{s_{t-1}^1} p(s_t^1|s_{t-1}^1) p^{a_{t-1}}(o_{t-1}|s_{t-1}^1) p^{a_{1:t-2}}(s_{t-1}^1|o_{1:t-2})}{\sum_{s_t^1} \sum_{s_{t-1}^1} p(s_t^1|s_{t-1}^1) p^{a_{t-1}}(o_{t-1}|s_{t-1}^1) p^{a_{1:t-2}}(s_{t-1}^1|o_{1:t-2})}$$

Horvath et al. (2021)

Theorie

Künstliche Intelligenz - Artificial Agent

$$\mathsf{M}_{\mathsf{Agent}} := (S, A, R, O, p(s_1^1), p(s_{t+1}^1|s_t^1), p^{a_t}(o_t|s_t^1), p^{a_t}(r_t|s_t^1), v, d)$$

- Handlungswertungsfunktion

$$v : A \times [0,1] \to \mathbb{R}, (a,b) \mapsto v(a,b)$$

- Entscheidungsfunktion

$$d : \mathbb{R} \to A, v(\cdot, b) \mapsto d(v(\cdot, b)) := \arg\max_{a \in A} v(a,b)$$

Horvath et al. (2021)

Theorievarianten

A1 | Gewinnmaximierender Agent

$$v_{\text{A1}}(a,b) := b\mathbb{E}_{p^a(r_t|s_t^1=1)}(r_t) + (1-b)\mathbb{E}_{p^a(r_t|s_t^1=2)}(r_t)$$

$\Rightarrow$ Erwartete Belohung von a unter momentaner Zustandsschätzug $b_t = b$

A2 | Informationsmaximierender Agent

$$v_{\text{A2}}(a,b) := \sum_{o_t} p_{a_{1:t-1},a_t=a}(o_t|o_{1:t-1})\mathsf{KL}\left(p_{a_{t-1},a_t=a}(s_{t+1}^1|o_{1:t-1},o_t)\|p_{a_{1:t-1}}(s_t^1|o_{1:t-1})\right)$$

$\Rightarrow$ Erwartete Bayesianische Überaschung von a unter momentaner Zustandsschätzug $b_t = b$

A3 | Gewinn- und informationsmaximierender Agent

$$v_{\text{A3}}(a,b) := \lambda v_{\text{A1}}(a,b) + (1-\lambda)v_{\text{A2}}(a,b)$$

$\Rightarrow$ Gewichtete Kombination der beiden Theoriealternativen

Horvath et al. (2021)

Datenvorhersage
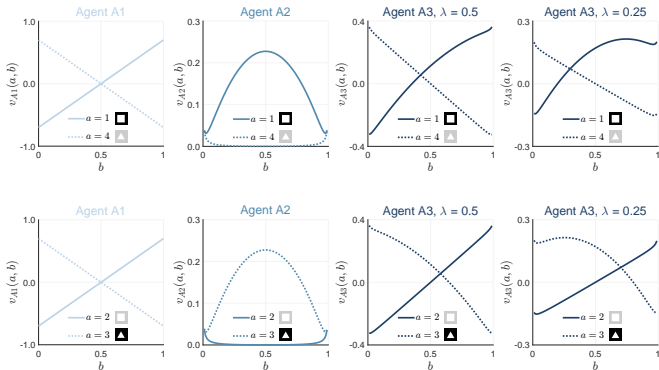
Horvath et al. (2021)

Datenanalyse

Horvath et al. (2021)

Entwicklung mechanistischer neuropsychologischer Modelle
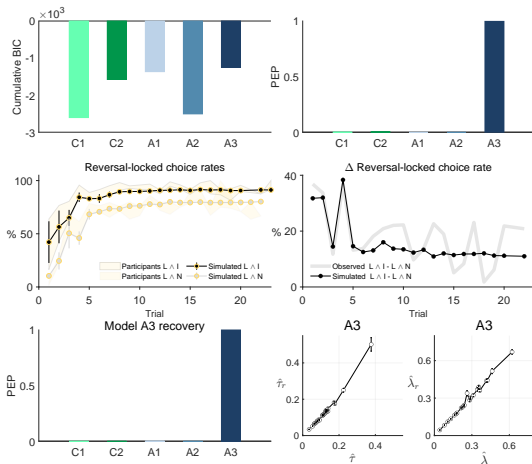
RESEARCH ARTICLE

Neural surprise in somatosensory Bayesian learning

Sam Gijsen[1,4]*, Miro Grundei[1,4]*, Robert T. Lange[2,5], Dirk Ostwald[3], Felix Blankenburg[1]

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Abstract

Tracking statistical regularities of the environment is important for shaping human behavior and perception. Evidence suggests that the brain learns environmental dependencies using Bayesian principles. However, much remains unknown about the employed algorithms, for somesthesis in particular. Here, we describe the cortical dynamics of the somatosensory learning system to investigate both the form of the generative model as well as its neural surprise signatures. Specifically, we recorded EEG data from 40 participants subjected to a somatosensory roving-stimulus paradigm and performed single-trial modeling across peri-stimulus time in both sensor and source space. Our Bayesian model selection procedure indicates that evoked potentials are best described by a non-hierarchical learning model that tracks transitions between observations using leaky integration. From around 70ms post-stimulus onset, secondary somatosensory cortices are found to represent confidence-corrected surprise as a measure of model inadequacy. Indications of Bayesian surprise encoding, reflecting model updating, are found in primary somatosensory cortex from around 140ms. This dissociation is compatible with the idea that early surprise signals may control subsequent model update rates. In sum, our findings support the hypothesis that early somatosensory processing reflects Bayesian perceptual learning and contribute to an understanding of its underlying mechanisms.

Gijsen et al. (2021)

Theorie | The Bayesian Brain Hypothesis

General framework

https://doi.org/10.3389/fnrgo.2021.718699
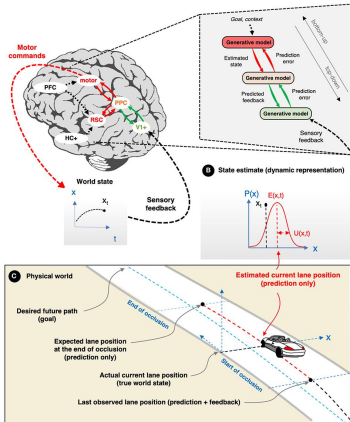
Kortikale und EEG Aktivität

https://doi.org/10.3389/fneur.2014.00228
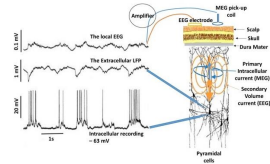
EEG Aktivität und Prädiktionsfehler

$$\text{BS}(y_t) \coloneqq \text{KL}(p(s_{t-1}|y_{1:t-1})||p(s_t|y_{1:t})))$$

https://doi.org/10.1371/journal.pcbi.1008068
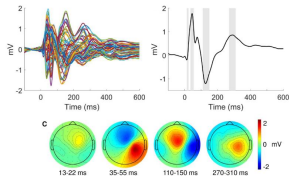
Helmholtz (1867), Friston (2005), Ostwald et al. (2012), Gijsen et al. (2021)

Experimentelle Simulation

Ostwald et al. (2012), Gijsen et al. (2021)

Entwicklung mechanistischer neuropsychologischer Modelle

Experimentelle Simulation
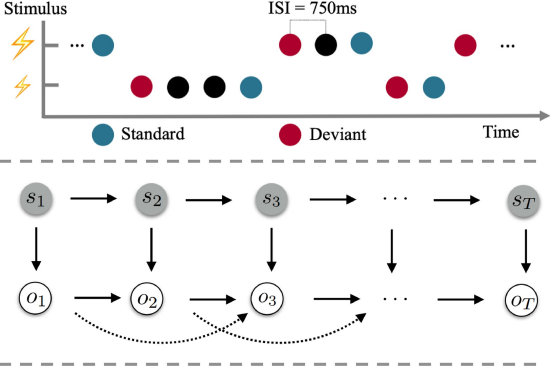
Ostwald et al. (2012), Gijsen et al. (2021)

Theorie
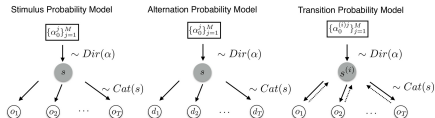
Fig 2. **Dirichlet-Categorical model as a graphical model.** Left: The stimulus probability model which tracks the hidden state vector determining the sampling process of the raw observations. Middle: The alternation probability model which infers the hidden state distribution based on alternations of the observations. Right: The transition probability model which assumes a different data-generating process based on the previous observations. Hence, it infers M sets of probability vectors α.

Datenvorhersage
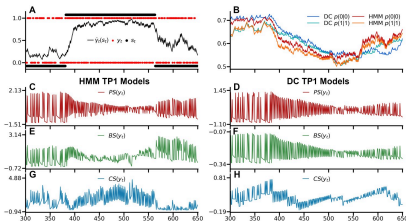
Fig 5. **Surprise readouts.** A) Example sequence with o_t in black, with $s_t = 0$ for the slow-switching regime and $s_t = 1$ for the fast switching regime, and the HMM filtering posterior $\hat{\gamma}_t(s_t)$ in between. The rare catch-trials are not plotted to facilitate a direct comparison between the HMM and DC models. B) The normalized probability estimates of the HMM TP$_1$ and DC TP$_1$ model with an observation half-life of 95, displaying differences in estimates arising from different adaptations to regime switches. C,E,G) The z-scored surprise readouts of the HMM TP$_1$ models: predictive surprise (PS), Bayesian surprise (BS), and confidence-corrected surprise (CS). D,F,H) The z-scored surprise readouts of the DC TP$_1$ models.

Gijsen et al. (2021)

Datenanalyse
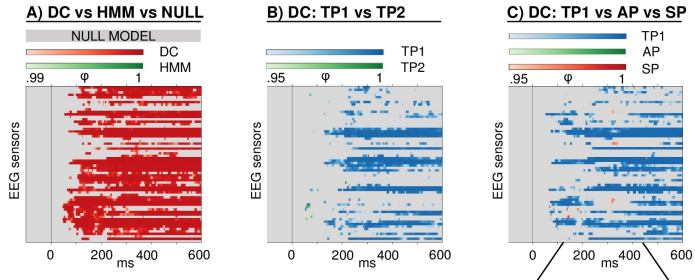
Fig 10. Modeling results. Exceedance probabilities (φ) resulting from the random-effects family-wise model comparison. (A) Dirichlet-Categorical (DC) model, Hidden Markov Model (HMM) and null model family comparison, thresholded at $\varphi > 0.99$ and applied for data reduction at all further levels. (B) Family comparison within the winning DC family, thresholded at $\varphi > 0.95$: first and second order transition probability models (TP$_1$, TP$_2$). (C) Family comparison within the winning DC family, thresholded at $\varphi > 0.95$: first order transition probability (TP$_1$), alternation probability (AP) and stimulus probability (SP) models and applied at the final level.

Gijsen et al. (2021)

Einführung

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Beispiele anwendungsorientierter psychologischer Forschung

Selbstkontrollfragen

Research report

Internet-based versus face-to-face cognitive-behavioral intervention for depression: A randomized controlled non-inferiority trial

Birgit Wagner [a,*], Andrea B. Horn [b], Andreas Maercker [b]

[a] Department of Psychosomatic Medicine and Psychotherapy, University of Leipzig, Semmelweisstr. 10, 04103 Leipzig, Germany
[b] Department of Psychology, University of Zurich, Binzmühlstr. 14/17, 8050 Zurich, Switzerland

ABSTRACT

Background and aims: In the past decade, a large body of research has demonstrated that internet-based interventions can have beneficial effects on depression. However, only a few clinical trials have compared internet-based depression therapy with an equivalent face-to-face treatment. The primary aim of this study was to compare treatment outcomes of an internet-based intervention with a face-to-face intervention for depression in a randomized non-inferiority trial.
Method: A total of 62 participants suffering from depression were randomly assigned to the therapist-supported internet-based intervention group ($n=32$) and to the face-to-face intervention ($n=30$). The 8 week interventions were based on cognitive-behavioral therapy principles. Patients in both groups received the same treatment modules in the same chronological order and time-frame. Primary outcome measure was the Beck Depression Inventory-II (BDI-II); secondary outcome variables were suicidal ideation, anxiety, hopelessness and automatic thoughts.
Results: The intention-to-treat analysis yielded no significant between-group difference (online vs. face-to-face group) for any of the pre- to post-treatment measurements. At post-treatment both treatment conditions revealed significant symptom changes compared to before the intervention. Within group effect sizes for depression in the online group ($d=1.27$) and the face-to-face group ($d=1.37$) can be considered large. At 3-month follow-up, results in the online group remained stable. In contrast to this, participants in the face-to-face group showed significantly worsened depressive symptoms three months after termination of treatment ($t=-2.05$, $df=19$, $p<.05$).
Limitations: Due to the small sample size, it will be important to evaluate these outcomes in adequately-powered trials.
Conclusions: This study shows that an internet-based intervention for depression is equally beneficial to regular face-to-face therapy. However, more long term efficacy, indicated by continued symptom reduction three months after treatment, could be only be found for the online group.

Wagner, Horn, and Maercker (2014)

Evidenzbasierte Evaluation von Psychotherapieformen bei Depression

Welche Therapieform ist bei Depression wirksamer?

Online Psychotherapie

Klassische Psychotherapie

Evidenzbasierte Evaluation von Psychotherapieformen bei Depression

Becks Depressions-Inventar (BDI) zur Depressionsdiagnostik

0 - 8 keine Depression

9 - 13 minimale Depression

14 - 19 leichte Depression

20 - 28 mittelschwere Depression

29 - 63 schwere Depression

Experimentelle Simulation

- Zufällige Zuordnung mittelschwer Depressionserkrankter zu Online vs. Klassisch

- Im Wesentlichen identisches Behandlungsprotokoll in beiden Gruppen

  - 8 Wochen Kognitive Verhaltenstherapie nach Hautzinger (2021).

  - Im Online Kontext nur schriftliches Feedback.

Theorie

- Es gibt Evidenz das internet-basierte Interventionen effektiv sind.

- Es gibt Evidenz das Therapeuten-geleitete effektiver als selbstgeleitete Interventionen sind.

Datenvorhersage

- Die BDI-Differenzen zwischen Prä- und Posttherapie unterscheiden sich nicht.

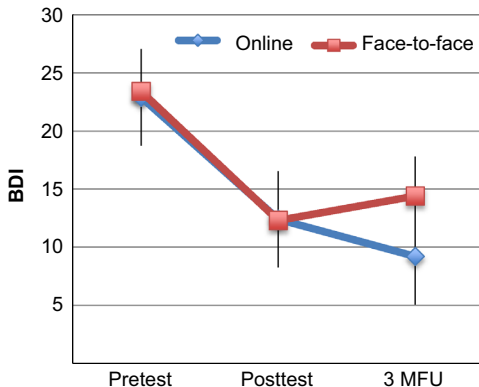Wagner, Horn, and Maercker (2014)

Datenanalyse

Fig. 2. Online intervention in comparison to a face-to-face group measured with the Beck Depression Inventory (BDI-II) at pretest, posttest and 3-months-follow-up, including standard error.

Wagner, Horn, and Maercker (2014)

Persönlichkeitspsychologie

Emotionsforschung

SPIEGEL Netzwelt

Manipulierte Timeline

Facebook kann auf Gefühle seiner Nutzer einwirken

Wissenschaftler machten ein Experiment mit Facebook-Nutzern: Eine Woche lang bekamen 300.000 von ihnen weniger Postings mit emotionalen Inhalten zu sehen als andere. Die Folgen waren deutlich messbar.

Von **Holger Dambeck**
04.06.2014, 07:36 Uhr

RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES

Experimental evidence of massive-scale emotional contagion through social networks

Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock Authors Info & Affiliations

Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 25, 2014 (received for review October 23, 2013)

June 2, 2014 | 111 (24) 8788-8790 | https://doi.org/10.1073/pnas.1320040111

THIS ARTICLE HAS BEEN CORRECTED +

CORRECTION

Editorial Expression of Concern: Experimental evidence of massive-scale emotional contagion through social networks

July 3, 2014 | 111 (29) 10779 | https://doi.org/10.1073/pnas.1412469111

PSYCHOLOGICAL AND COGNITIVE SCIENCES PNAS is publishing an Editorial Expression of Concern regarding the following article: "Experimental evidence of massive-scale emotional contagion through social networks," by Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock, which appeared in issue 24, June 17, 2014, of *Proc Natl Acad Sci USA* (111:8788-8790; first published June 2, 2014; 10.1073/pnas.1320040111). This paper represents an important and emerging area of social science research that needs to be approached with sensitivity and with vigilance regarding personal privacy issues.

Questions have been raised about the principles of informed consent and opportunity to opt out in connection with the research in this paper. The authors noted in their paper, "[The work] was consistent with Facebook's Data Use Policy, to which all users agree prior to creating an account on Facebook, constituting informed consent for this research." When the authors prepared their paper for publication in PNAS, they stated that: "Because this experiment was conducted by Facebook, Inc. for internal purposes, the Cornell University IRB [Institutional Review Board] determined that the project did not fall under Cornell's Human Research Protection Program." This statement has since been confirmed by Cornell University.

Obtaining informed consent and allowing participants to opt out are best practices in most instances under the US Department of Health and Human Services Policy for the Protection of Human Research Subjects (the "Common Rule"). Adherence to the Common Rule is PNAS policy, but as a private company Facebook was under no obligation to conform to the provisions of the Common Rule when it collected the data used by the authors, and the Common Rule does not preclude their use of the data. Based on the information provided by the authors, PNAS editors deemed it appropriate to publish the paper. It is nevertheless a matter of concern that the collection of the data by Facebook may have involved practices that were not fully consistent with the principles of obtaining informed consent and allowing participants to opt out.
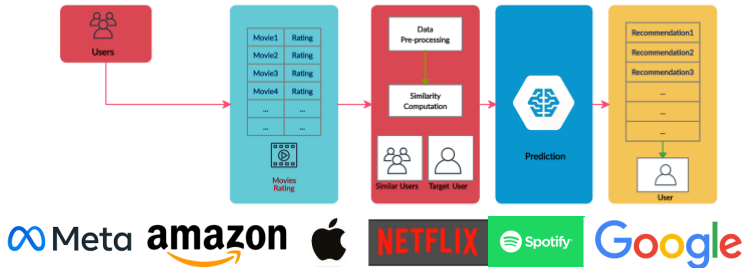
Selbstkonzeptforschung

Kaufentscheidungsverhalten

https://towardsai.net/

Sozialverhalten

Einführung

Beispiele grundlagenorientierter psychologischer Forschung

Beispiele anwendungsorientierter psychologischer Forschung

Selbstkontrollfragen

1. Definieren Sie den Begriff Psychologie.

2. Nennen Sie vier Aspekte psychologischer Wissenschaft.

3. Erläutern Sie den Begriff der psychologischen Grundlagenforschung.

4. Erläutern Sie den Begriff der anwendungsorientierten psychologischen Wissenschaft.

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Wagner, Birgit, Andrea B. Horn, and Andreas Maercker. 2014. "Internet-Based Versus Face-to-Face Cognitive-Behavioral Intervention for Depression: A Randomized Controlled Non-Inferiority Trial." *Journal of Affective Disorders* 152–154 (January): 113–21. https://doi.org/10.1016/j.jad.2013.06.032.