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NEURO-ALGORITHMIC CONSUMER INSIGHTS: INTEGRATING ARTIFICIAL INTELLIGENCE, NEUROMARKETING, AND PERSONALIZED MARKETING - A CONCEPTUAL FRAMEWORK AND SIMULATION-BASED PROOF OF CONCEPT

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ABSTRACT

There is an increasing tendency in marketing practices of using artificial intelligence (AI) for message personalization while neuromarketing can provide data on consumer behavior that are impossible to obtain from self-reports. Despite similarities, the fields have been developing separately. This paper presents the Neuro-Algorithmic Consumer Insights (NACI) model where AI-based personalization leads to physiological responses (arousal, motivation for an approach, attention), which influence the results from self-reports of emotional response to purchase execution. The results can be further used as predictors of purchase behavior. For the verification of the proposed model, an experiment was conducted with 600 subjects (289 personalized messages and 311 generic). The analysis included Welch tests with Holm correction, hierarchical regression, bootstrapped mediation analysis, and multiple logistic regression. It was demonstrated that personalization leads to arousal ($d = 0.45$), greater left frontal alpha asymmetry ($d = 0.431$), attention ($d = 0.24$), engagement ($d = 0.40$), and intention to purchase ($d = 0.37$). It was found that physiological variables can account for 24.1% of variability in intention to purchase over demographic and personalization variables ($F(4, 590) = 52.11$, $p < .001$). It is estimated that attention and engagement accounted for 59 percent of the overall effect. Incorporation of physiological factors resulted in the increase in cross-validated AUC for purchase from .61 to .69 according to logistic regression. The results indicate that the designed pipeline reveals previously confirmed effects but does not yield novel insights. The article also reviews limitations of the research and deals with ethical issues raised by it.
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1. Introduction

The main purpose of consumer research is based on what customers say in their responses to interviews and surveys. Most of the time, consumers make their decisions based on randomness (Kahneman, 2011). That is why neuromarketing has developed a set of methods of neuromarketing (fMRI, EEG, eye movement, measuring electrical activity on the skin, etc.) to solve marketing problems (Fugate, 2007; Lee et al., 2007). Studies conducted using brain scans reveal that brain reactions measured on small samples of participants can predict the behavior of the whole population (Berns & Moore, 2012; Boksem & Smidts, 2015; Falk et al., 2012).
Meanwhile, artificial intelligence has become the most important tool for personalized marketing. Such systems as machine learning personalize consumers' marketing messages and offers (Davenport et al., 2020; Huang & Rust, 2021; Kumar et al., 2019). Moreover, using digital footprints provides information about consumers' preferences (Kosinski et al., 2013; Matz et al., 2017). Behavioral data can show what consumers did but providing the reason for the success of a particular marketing technique is difficult. Critiques of neuromarketing center on issues such as limited sample sizes, limitations of laboratory conditions, and the inability to conduct large-scale tests (Ariely & Berns, 2010; Plassmann et al., 2015). AI's advantages (size and real-time optimization) match neuromarketing's disadvantages, while neuromarketing's advantage (the ability to measure implicit response) coincides with the shortcoming of AI personalization. Thus, their complementary nature becomes a reason for an integrated approach.

1.1 Gap and Contribution

Earlier research has looked into the results of the personalization of AI or the physiological repercussions of advertising, but there has not been much research into the connection between these two aspects or testing if physiological signals can strengthen prediction accuracy of the algorithms being used. This paper presents (a) the NACI," which is the conceptual model; (b) five hypotheses that can be tested; (c) a two-step analysis plan involving explanatory (regression and mediation) and predictive (cross-validated machine learning) methods; and (d) an ethical and a research plan.

1.2 Questions of research

- RQ1. Will the AI-driven personalization lead to greater physiological and emotional responses compared to generic promotional messages?
- RQ2. Will these responses serve as mediators for the impact of personalization on purchase intentions?
- RQ3. Are the physiological characteristics a better predictor of the purchase intentions than behavioral and demographic indicators?

2. Literature Review and Hypotheses

2.1 AI and Customized Marketing

In marketing, one can encounter various applications of AI that fall into three different categories: mechanical processes (automation), cognitive functions (analytics and forecasting), and emotional responses (recognizing and responding to feelings) (Huang & Rust, 2021). Personalization solutions choose information based on the user's characteristics by using techniques like collaborative filtering and tree ensembles (Breiman, 2001; Friedman, 2001). Studies show that personalization yields better rates of engagement and conversion if the messages are in accordance with psychological profiles (Matz et al., 2017) and if consumers see them as meaningful rather than intrusive (Aguirre et al., 2015; Kumar et al., 2019). At the same time, behavioral traces are not sufficient as they provide only outcome data and do not reflect inner experiences responsible for clicks.

2.2 Neuromarketing and physiological measures

Three categories of measures are informative. Electrodermal activity (EDA) provides a measure of sympathetic arousal (Boucsein, 2012). Frontal alpha asymmetry (FAA) obtained from EEG has gained acceptance as a measure of the approach-versus-withdrawal motivation, although some debate its interpretation (Harmon-Jones et al., 2010). Eye movement recording provides a measure of visual attention. Neural activity in the brain regions related to reward and valuation systems is linked to acquisition and later success in the market (Falk et al., 2012; Knutson et al., 2007). Neuro-physiological measures can provide additional insights relative to traditional measures of advertising (Venkatraman et al., 2015). Brain data provide evidence for effects that may be missed by self-reports (Plassmann et al., 2012).

2.3 The Neuro-Algorithmic Loop

The operation of a neuro-algorithmic system involves a loop: (1) an algorithm selects a specific stimulus; (2) sensors record arousal, attention, and approach; (3) these parameters determine emotional engagement; (4) engagement predicts intention and behavior; and (5) predictions alter the algorithm. Only a limited number of studies have examined the process of emotional engagement separately.

2.4 Conceptual model and hypotheses

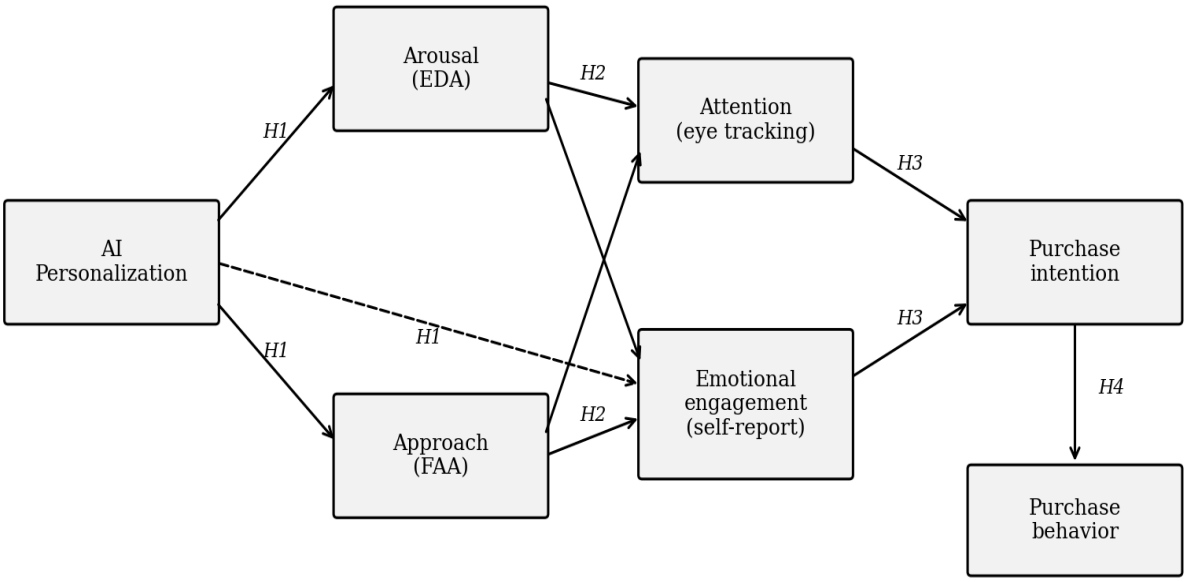


Figure 1: The Neuro-Algorithmic Consumer Insight (NACI) Model, where the direct effect of personalization on engagement is indicated using a dashed line and the prediction of purchase is labeled H5 but not shown in the diagram.

• H1: It is hypothesized that personalized advertisements will lead to higher arousal, motivation to act, attention, engagement, and purchase intention as compared to generic advertisements.

• H2: It is predicted that the level of arousal and motivation to act will positively forecast the degree of attention and emotional engagement.

• H3: It is believed that both attention and engagement will mediate in part the influence of personalization on purchase intention.

• H4: Purchase intention is supposed to have a positive impact on the actual purchase behaviors.

• H5: Physiological features will enable out-of-sample prediction of purchase to be performed successfully in addition to demographic and personalized indicators.

Since the data is based on simulations, every hypothesis will serve as a target for recovery by examining whether the analysis plan identifies the effect which is embedded in the model that generates the data.

3. Research Methodology

3.1 Design

This study employs a between-subjects approach, where subjects are assigned randomly to conditions featuring either an AI-personalized advertisement (containing content, images, or offers determined by means of a recommendation model based on subjects' profiles) or a generic advertisement of the same type. In this setup we thus get 289 observations in the personalized condition and 311 observations in the generic condition (total N = 600). With these number of subjects, the power to detect d = 0.25 at α = .05 (two-tailed) is .86, while the minimum detectable effect with 80% power is at d = 0.23; power for d = 0.20 is only .69.

3.2 Variables and operationalization

Construct	Role	Operationalization (for real data)
Personalization (ai)	Independent	0 = generic, 1 = AI-personalized
Arousal (eda)	Physiological	Baseline-corrected skin conductance, z-scored
Approach (fal)	Physiological	EEG frontal alpha asymmetry (F4–F3), z-scored
Attention (att)	Physiological/behavioral	Eye-tracking dwell time on brand/offer area, z-scored
Emotional engagement (emo)	Mediator, self-reported	Multi-item affective engagement scale, z-scored; a measure separate from the physiological indicators
Purchase intention (pi)	Attitudinal outcome	Multi-item scale, z-scored
Purchase (buy)	Behavioral outcome	1 = purchased in follow-up choice task, 0 = did not
Controls	Covariates	Age, income (z), gender (0/1), stated brand preference (z)

3.3 Data generation

Data were developed in Python using the seed value of 2026 and from the linear structural equation model in accordance with Figure 1. Personalization in the model increased arousal (β = .45) and approach (β = .40) variables.

Arousal (β = .35) and approach (β = .30) caused attention to be increased. Additionally, arousal (β = .30), approach (β = .35), and personalization (β =.15) promoted enhanced engagement. Finally, the intention is impacted by personalization (β = .10), attention (β

= .30), engagement (β = .35), stated preferences (β = .20), and income (β = .05). Purchase variable was drawn from the logistic function about intention, engagement, attention, and stated preferences. Age (18-54) M = 35.6, SD = 10.6, income gender (53% coded 1), and preferences are random values.

3.4 Analytical Plan

H1: There will be Welch t-tests with Cohen's d, as well as Holm (1979) corrections for the five outcomes, and a two-proportion test for purchase.

H2: There will be OLS regression of attention and engagement on arousal, approach, and condition.

H3: A hierarchical OLS regression will be performed on intention after controlling during Step 1, then adding personalization in Step 2, and finally introducing the four physiological/affective variables in Step 3, finally performing a parallel mediation test with 2000-resample percentile bootstrap intervals (Hayes, 2022).

H4: There will be logistic regression of purchase on intention while controlling for condition and covariates in the analysis.

H5: There will be logistic regression studies using random forest (Breiman, 2001) with gradient boosting (Friedman, 2001) methods for predicting purchase; the method will perform 10 times of stratified 5-fold cross-validation; 5 features will be used in behavioral/demographic studies, and augmented studies will use 9 features; AUC will be used in these studies.

Assumption checking for this analysis will include variance inflation factors, residuals from Breusch–Pagan and Shapiro–Wilk tests during testing.

Software: The software to be used in this study will include Python with NumPy, pandas, SciPy, statsmodels and scikit-learn (Pedregosa et al., 2011).

4. Results (Simulation)

4.1 Correlations

Table 1 *Correlations Among Simulated Variables (N = 600)*

	1	2	3	4	5	6
1. Personalization	—					
2. Arousal	.22	—				
3. Approach	.21	−.01	—			
4. Attention	.12	.31	.24	—		
5. Emotional engagement	.20	.35	.32	.18	—	
6. Purchase intention	.18	.21	.23	.39	.42	—
7. Purchase (0/1)	.11	.21	.14	.25	.26	.46

Note. $|r| \geq .08$ is significant at $p < .05$ (two-tailed).

The Pearson correlation coefficients of the simulated variables reflected in Table 1 were accumulated from 600 observations. The findings showed mainly positive relationships between the variables. Personalization has weakly positive correlations with Arousal (r = .22), Approach (r = .21), Attention (r = .12), Emotional Engagement (r = .20), Purchase Intention (r = .18), and Purchase (r = .11). Arousal positively correlates with Attention (r = .31), Emotional Engagement (r = .35), Purchase Intention (r = .21), and Purchase (r = .21), while the relationship with Approach is insignificant (r = −.01). Approach reveals positive correlations with Attention (r = .24), Emotional Engagement (r = .32), Purchase Intention (r = .23), and Purchase (r = .14). Furthermore, Attention is positively correlated with Purchase Intention (r = .39) and Purchase (r = .25), while Emotional Engagement is positively correlated with Purchase Intention (r = .42), and Purchase (r = .26). The strongest relationship is with regards to Purchase Intention and Purchase (r = .46) what indicates that purchase intention significantly impacts purchase behavior. In accordance with the significance rule of $|r| \geq .08$ at $p < .05$, all the relationships described above are statistically significant with the sole exception of the Arousal–Approach relationship (r = −.01). In brief, the study findings demonstrate that the variables used in the simulation are generally positively related, with the focus on Attention, Emotional Engagement, and Purchase Intention as the main factors behind purchase behavior.

4.2 H1: Group differences

Table 2 *Personalized (n = 289) vs. Generic (n = 311) Advertising*

Variable	Generic *M*	Personalized *M*	Welch *t*	Cohen's *d* [95% CI]	Holm-adj. *p*
Arousal	−0.05	0.42	5.46	0.45 [0.28, 0.61]	< .001
Approach	0.02	0.44	5.32	0.43 [0.27, 0.60]	< .001
Attention	0.01	0.29	2.98	0.24 [0.08, 0.40]	.003
Engagement	0.02	0.46	4.92	0.40 [0.24, 0.56]	< .001
Intention	−0.01	0.41	4.48	0.37 [0.21, 0.53]	< .001

Purchase rates were 55.0% (159/289) for personalized and 44.4% (138/311) for generic advertising, $z = 2.61$, $p = .009$. H1 was recovered. Note that the lower confidence limit for attention ($d = 0.08$) shows that this effect is estimated imprecisely at this sample size.

Table 2 illustrates a comparison of results of personalized advertising and ordinary advertising to a group of 600 individuals. It was discovered that personalized advertising results in the highest levels of Arousal (M = 0.42), Approach (M = 0.44), Attention (M = 0.29), Engagement (M = 0.46) and Purchase Intention (M = 0.41) compared to ordinary advertising that produced the following mean values −0.05 for Arousal, 0.02 for Approach, 0.01 for Attention, 0.02 for Engagement and −0.01 for Purchase Intention. Welch's tests have indicated that there were significant differences for all the factors in question with p < .001 for Arousal, Approach, Engagement

and Intention and p = .003 for Attention. The effect has varied from small to medium in terms of magnitude with Cohen's d being 0.24 for Attention, 0.37 for Intention, 0.40 for Engagement, 0.43 for Approach and 0.45 for Arousal. Also, the purchase results have been increased for personalized advertising leading to 55.0% (159/289) purchase results than ordinary advertisement leading to 44.4% (138/311). Overall, there is evidence that personalized advertising was leading to increased emotional, cognitive and behavioral responses together with increased rate of purchases as opposed to their regular advertising.

4.3 H2: Physiology → attention and engagement

Table 3 *Regressions of Attention and Engagement on Physiological Predictors*

Outcome	Predictor	*B*	*SE*	*t*	*p*
Attention (R^2 = .156)	Personalization	0.003	0.090	0.03	.978
	Arousal	0.334	0.041	8.16	< .001
	Approach	0.277	0.044	6.24	< .001
Engagement (R^2 = .229)	Personalization	0.130	0.085	1.53	.126
	Arousal	0.352	0.039	9.14	< .001
	Approach	0.355	0.042	8.49	< .001

Arousal and approach predicted both outcomes, and personalization showed no direct effect once they were included, so its influence on attention and engagement runs through the physiological pathway. H2 was recovered.

The regression results that were presented in Table 3 assessed the influence of personalization, arousal, and approach on attention and engagement. The model accounted for 15.6% of the variance in the case of Attention (R^2 = .156). Arousal (B = 0.334, SE = 0.041, t = 8.16, p < .001) and Approach (B = 0.277, SE = 0.044, t = 6.24, p < .001) turned out to be significant predictors; on the other hand, Personalization did not prove to be significant (B = 0.003, p = .978). The case with Engagement required a different approach. The model accounted for 22.9% of the variance in this case (R^2 = .229), meaning that Arousal (B = 0.352, SE = 0.039, t = 9.14, p < .001) and Approach (B = 0.355, SE = 0.042, t = 8.49, p< .001) possessed statistically significant effects; Personalization, however, did not show statistically significant results (B = 0.130, p = .126). It is interesting to note that the influence of physiological variables, particularly arousal and approach, on attention and engagement proved significant, while personalization did not exert any direct influence once the physiological aspects were taken into account. Therefore, H2 receives evidence in terms of the assumption that the link between personalization and mentioned variables is most probably provided by physiological pathway.

4.4 H3: Hierarchical regression and mediation

Table 4 *Hierarchical Regression Predicting Purchase Intention*

Step	Predictors added	R^2	Adj. R^2
1	Age, income, gender, stated preference	.045	.039
2	Personalization	.079	.071
3	Arousal, approach, attention, engagement	.320	.309

Step 2 → 3: ΔR^2 = .241, $F(4, 590) = 52.11$, $p < .001$.

The hierarchical regression findings for Purchase Intention are provided in Table 4. In Step 1, the variables measuring demographic information in addition to controls variables like age, income, gender as well as stated preference explained a mere 4.5% of purchase intentions (R^2 = .045; adjusted R^2 = .039). Upon the addition of Personalization in Step 2, the model explained 7.9% of the variance (R^2 = .079; adjusted R^2 = .071), which indicates that personalization has made additional contribution since its inclusion was beyond control variables. In Step 3, when Arousal, Approach, Attention and Engagement were included into the model, the level of explained variance improved to 32.0% (R^2 = .320; adjusted R^2 = .309). The improvement in the variance level from Step 2 to Step 3 was statistically meaningful with ΔR^2 = .241, F(4, 590) = 52.11, p < .001, meaning that variables that provide the physiological as well as psychological response to marketing efforts explained the remaining 24.1% of the variance in purchase intentions over and above the effect produced by demographics, stated preferences and Personalization. Overall, it can be stated that addition of arousal, approach, attention and engagement has significantly increased the explanatory power of the model in explaining purchase intention.

Table 5 *Step 3 Coefficients (DV = Purchase Intention)*

Predictor	*B*	*SE*	*t*	*p*
Stated preference	0.222	0.041	5.43	< .001
Personalization	0.205	0.083	2.47	.014
Arousal	−0.070	0.043	−1.64	.102
Approach	0.005	0.045	0.11	.912
Attention	0.335	0.038	8.90	< .001
Engagement	0.362	0.040	9.05	< .001

Note. Age, income, and gender were nonsignificant ($p > .59$). Variance inflation factors were ≤ 1.37; Breusch–Pagan ($p = .57$) and Shapiro–Wilk ($p = .87$) tests gave no sign of heteroscedasticity or non-normal residuals.

Table 5 continues with Step 3 regression coefficients for purchase intention. The influence of stated preference on purchase intention has become apparent (B = .222, SE = 0.041, t = 5.43, p < 0.001), whereas personalization has also exhibited a positive effect on purchase intention (B = 0.205, SE = 0.083, t = 2.47, p = 0.014). At the same time, arousal (B = -0.070, p = 0.102) and approach (B = 0.005, p = 0.912) were incapable of predicting the purchase intention since this process was controlled by other variables. Attention (B = 0.335, SE = 0.038, t = 8.90, p < 0.001) and engagement (B = 0.362, SE = 0.040, t = 9.05, p < 0.001) have become established positive predictors of outcome, meaning that the higher level of attention and engagement can contribute to larger purchase intention. Age, income, and gender are also found to be insignificant variables (p > .590) implying that these demographic factors are not causing

aspects of the purchase intention in the end model. The presence of VIF values (≤ 1.37) suggests that the issue of multicollinearity is not serious, as well as the Breusch–Pagan (p = 0.57) and Shapiro–Wilk (p = 0.87) show that there is no evidence for heteroscedasticity or serious non-normality of residuals.

Table 6 *Bootstrapped Mediation of Personalization → Purchase Intention (2,000 resamples)*

Path	Estimate	95% CI
Total effect	0.419	—
Direct effect	0.172	[0.014, 0.328]
Indirect via attention	0.090	[0.033, 0.153]
Indirect via engagement	0.158	[0.091, 0.230]
Total indirect (proportion of total)	0.247 (59%)	[39%, 94%]

Both indirect effects were significantly greater than zero and the direct effect stayed significant, thus confirming partial mediation (H3 confirmed). The percentage of mediation is also very vague (39%–94%) and has to be interpreted carefully. In real life data, causal mediation interpretation of mediators that are measured can be true only if it is assumed that there is no confounding between mediator and outcome from unmeasured third variable.

Table 6 illustrates results obtained from a bootstrapped mediation analysis. The research defined whether Attention and Engagement serve as mediators in the connection between Purchase Intention and Personalization, examining 2000 bootstrap resamples. Personalization was found to affect Purchase Intention to the extent of 0.419, while the direct effect was 0.172; its confidence interval was 0.014-0.328. The indirect effect of the variable did through attention made it equal to 0.090 with a confidence interval of 0.033-0.153, which suggests that the mediation took place since the confidence interval does not include zero. The indirect effect through engagement was equal to 0.158 while its confidence interval was 0.091-0.230, which suggests that mediation also happened. The overall total indirect effect was equal to 0.247 which accounts for nearly 59% of the overall effect; the bootstrapped interval is 39-94%. Thus, the results indicate that mediation happened since Attention and Engagement influence Purchase Intention indirectly. There is a direct effect implying that the mediation is not full, which shows that Personalization affects Purchase Intention directly in addition to the effects of mediators.

4.5 H4: Intent to purchase

In the logistic model controlling for such factors as preference, age, income, gender, and condition (intent in this case), the analysis indicated that intention was a strong predictor of purchase (OR = 2.65 per SD, 95% CI [2.18, 3.24], p < .001). When intention was included in the model, McFadden's pseudo-R^2 value was increased from .036 to .185. In this case, it was also established that condition did not predict purchase (p = .471), meaning that the effect of condition on purchase goes through intention.

4.6 H5: Predictive value of physiological features

Table 7 *Cross-Validated AUC for Purchase (10 × 5-fold; mean [SD across folds])*

Model	Behavioral/demographic	Augmented (+ 4 physiological/affective)	Mean gain
Logistic regression	.605 [.042]	.691 [.036]	.086
Random forest	.599 [.040]	.659 [.040]	.060
Gradient boosting	.585 [.046]	.665 [.040]	.080

The AUC gained from the logistic model, calculated using pooled out-of-fold predictions, was equal to 0.075 (with bootstrap 95% CI being between 0.032 and 0.115). The folds SD's are the SD's from repeated cross-validated folds because the underlying set used to create the pool is the same. Hypothesis 5 is accepted. Keeping in mind the way the data is generated (having linear effects and moderate size), the regularized linear model is not worse than the forest. In the previous experiment with the single split 70/30, the AUC gained by augmented logistic model was approximately equal to 0.72; in this case, the cross-validated estimate has more reliability.

4.7 Summary

Hypothesis	Recovered in simulation?
H1 Personalization ↑ responses and intention	Yes
H2 Arousal & approach → attention & engagement	Yes
H3 Partial mediation by attention & engagement	Yes
H4 Intention → purchase	Yes
H5 Physiological features improve prediction	Yes

The summary of the hypotheses reveals that all 5 hypotheses have been confirmed by the results of the simulation. H1 has been accepted due to a positive correlation of personalized advertisements with consumer behavior and purchase intention. H2 has been accepted due to a significant influence of arousal and approach on consumer attention and engagement. H3 has been confirmed, as the mediation analysis has shown partial mediation of the relationship between personalization and purchase intention by attention and engagement. H4 has been confirmed, as purchase intention has a positive correlation with actual purchase behavior. H5 has been

confirmed, as the incorporation of the physiological variables, arousal and approach, has increased explanatory potential regarding consumer behavior and purchase intention. In summary, the simulation outcomes have provided substantial supporting evidence for all the proposed interrelations of the variables studied.

5. Discussion and Conclusions

What the simulation shows. The application of the analytical procedure allows obtaining positive results even when the sample size is not big (in our case N=600). Moreover, the procedure yields meaningful effect and estimation results. Furthermore, it has shown several practical conclusions: 1) the attention effect is right at the edge of detection; 2) the mediation effect is extremely small; 3) the gain from predictive ability obtained in the case of single train-test split is overstated in comparison to the one obtained when the model is verified by repeated cross-validation.

What the simulation does not show. Despite the fact that the simulation yielded some promising results, it does not allow claiming that AI-generated personalization has impact on physiology of people in reality, does not prove that physiological indexes work as a means of mediation and does not show that the use of physiological data allows getting any real predictive ability. Each of the "positive" results is predetermined and does not allow achieving any reliable data.

Theoretical and managerial importance of validation of the results. The NACI framework provides the theoretical model for understanding why personalization works, connects "feeling AI" (Huang & Rust, 2021) with measurable indicators and suggests that When it comes to training and calibration, it should be noted that sensors are seldom present in real campaigns. Any project should regard the trade-offs of privacy and trust (Aguirre et al., 2015).

5.1 Limitations

1. Data was simulated and not obtained empirically; 2. Effect sizes were assumed, possibly in optimistic terms compared to noisy real signals; 3. Linear generation model is fit for linear estimators; 4. There is one stimulus and one exposure; 5. Nothing affected the results, no missing data or individual differences; 6. Mediation and prediction results were based on the assumption of the causal framework; 7. Consensus not reached about the meaning of FAA (Harmon-Jones et al., 2010).

6. Future Research Directions

1. Validation with actual data. A protocol has been established for experimentation with the use of EEG, EDA, and eye tracking involving a set of experiments that are pre-registered using a conservative estimate of effect sizes (e.g., d = 0.20 which requires a sample of 400 subjects). It would involve a mixed-model design utilizing various stimuli, as well as cross-validation with an untouched hold-out set.
2. Simulation protocols. Designing the study to account for errors in measurement, noise, nonlinearity, and missing data.
3. Forms of scalable approximators. Exploring whether or not the information from web cameras and portable devices such as EDA monitors and heart rate monitors or voice activity can be treated as sources of signals obtained in the laboratory under standard controlled conditions.
4. Closed-loop Adaptation. Bandit and reinforcement learning systems coupled with physiological feedback instead of optimizing pure behavior.
5. Heterogeneity and fairness. Performance distinction based on age, sex, culture, and neurodiversity, with potential bias.
6. Personalization paradox. Physiological indicators of reactance and privacy concern.
7. Cross-cultural work, with a focus on India and other markets that are mobile-first.
8. Ethics and regulations. Consents concerning neuro-data benchmark, prohibition of exploitation within vulnerable states, and explainability/compliance with applicable data protection law (e.g., GDPR; the Digital Personal Data Protection Act of India, 2023).
9. Long-term impact on brand image and loyalty and well-being.

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