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Digital Health Interventions to Improve Engagement in Preventive Care

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ABSTRACT

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Objective: This paper explores how these new digital health designs characteristics contribute to preventive care engagement, synthesizing behavioural, ethical, and emotional factors in one framework.
Methods: A cross-sectional design with validated constructs, and estimated with regression and moderation models by mean of EViews software.
Results: Results suggest that empathetic digital connections have the strongest impact on motivating preventive care usage, followed by ritualized nudges integrated in daily life, transparent consent processes, and calibrated friction signals. Crucially, all relationships are moderated by the Privacy personalization threshold, which indicates that personalization increases engagement up to the point beyond which the concerns over privacy over take the perceived value. Above this threshold, the gain from empathy, nudges, consent comfort, and care-related friction are increasingly eroded. This finding underscores the double-edged nature of personalization: while critical for engagement, it risks eroding trust if viewed as too intrusive.
Novelty: It leverages four new constructs Ritualised Micro-Nudge Fit, Friction-as-Care Signal, Consent comfort dynamics, and Agent Anticipatory Empathy and conceptualises privacy personalisation thresholds as moderation boundaries. The model innovatively combines nudge theory, privacy calculus, and affective computing in order to understand digital health engagement.
Implications for Research: The results contribute theoretically through the partial evidence that shows interaction of behavioural economics, emotional design and ethical governance in prevention. From a practical perspective, the study offers direction on developing empathetic, contextually embedded, privacy-sensitive as well as ethically-sound digital health interventions consisting of a blueprint for sustaining global long-term preventive health participation.

1. Introduction

Digital health interventions have become increasingly integral in the transition towards preventive medicine, providing scalable strategies to improve individual engagement and long-term health. Health, telemedicine, and AI-driven reminders have the potential to break down barriers to preventive care, and with the COVID-19 experience, their widespread adoption was accelerated and their impact will change the patient-provider interaction moving forward (Huang et al., 2022; Morey et al., 2025). More recently, the combination of micro-nudges 2023 real time behavior prompts, and AI based personalization has been found to be highly associated with increased screening adherence and uptake vacienes (Chu et al., 2025; Unlu et al., 2025). Nevertheless, the continued involvement is problematic, as attrition often exceeds 60%, within the first 3 month of use of digital health apps, thus, exposing an urgent gap between use of adoption and meaningful preventive behaviours (Matos Fialho et al., 2025; Prior et al., 2024). This paradox of rapid tech progress but low user persistence indicates that it is not enough to just to digitize preventive

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care without thoughtful design features built into it that capture these contextual, psychological and ethical dimensions of engagement. Hence, the search for new determinants of preventive care use is not only timely, but also crucial to change the levels of preventive care use globally.

The trade off between personalization, privacy, and user trust is a key challenge in digital health. Personalised digital interventions have improved efficacy when compared to non-grandma reminders, but users may feel overly cared for, leading to a lack of adherence (Bender, 2018; Probst et al., 2024; Reynolds 3rd et al., 2022). This is further exacerbated where preventive care is long term and demands multiple interactions – users may experience ‵inevitable burnout′ with too many push notifications, or may reject push notifications as being manipulative rather than supportive (Gavilan & Martinez-Navarro, 2022; Karwowski et al., 2025; Perski et al., 2024; Strauss, 2024). There are ethical concerns as well regarding the possibility of misuse of personal health data in preventive platforms which could undermine trust in health technologies if safeguards are not sufficiently underscored (Ahmad, 2025; Liu et al., 2024; Sivakumar et al., 2024). These tensions suggest that there is a need for research to move beyond standard usability and effectiveness metrics to the mechanisms by which technically and informatically enabled preventive behaviours can be leveraged across diverse populations.

Multiple theoretical backgrounds underlie the prospective variables of this study. Nudge theory when demonstrates how marginal design options affect choice without constraining options (Thaler & Sunstein, 2009). Multiple studies have shown that perceived usefulness and ease of use are key drivers of user engagement in digital settings (Venkatesh et al., 2003). Privacy calculus theory also explains how people weigh the cost to benefit of disclosing private information (Dinev & Hart, 2006). Last, the affective computing literature supports the idea that empathic AI can predict and respond to emotional states as a means to enhance engagement and adherence (Picard, 2003). Collectively, these frameworks offer a strong base on which to consider how micro-nudge fit, friction-as-care signals, consent dynamics, and anticipatory empathy may influence preventive care engagement as moderated by privacy–personalization tension.

Although there have been numerous studies on digital health interventions, large variations still exist in the body of evidence. Some studies have found robust positive effects of personalized nudges and reminders on preventive adherence (Aigbonoga et al., 2025; Desoky et al., 2025; Paltin et al., 2025; Tan et al., 2025), whereas others point to high attrition and dwindling engagement over time, indicating poor sustainability (Bion & Turner, 2025; Chen et al., 2025; Obeng et al., 2025; Yang et al., 2025). At the proximity level, while some studies demonstrate that lowering friction increases adoption of digital health (Aungst, 2025; Bion & Turner, 2025; Jung et al., 2025), others find low or even negative effects on trust and perceived credibility (Chung et al., 2025; Krishna et al., 2023; Narayan et al., 2025). Along the privacy dimension, studies show that data-sharing concerns are a deterrent to sharing behavior Kim et al. (2025), but in turn users are willing to consent when there is transparency and perceived value (Sharon & Lucivero, 2019; Huang et al., 2023). The contribution of AI empathy is also debated: while empathetic exchanges contribute to engagement (Graffigna et al., 2020), anthropomorphism skepticism occasionally decreases trust (Laranjo et al., 2018). Inconsistent results among these studies reveal an important research gap: there is a dearth of holistic models to simultaneously query and relate micro-nudge alignment with rituals, intentional nudge as a care-statement, dynamic consent comfort, and foresightful empathy with privacy–personalization tension as a moderator. To address this gap, this study contributes a novel theoretical model that combines insights from the theory of behavioural economics, information systems and theory of affective computing to provide a new perspective in understanding sustainable engagement in preventive care in digital health.

Addressing these voids, the current research seeks to investigate the impact of Ritualized Micro-Nudge Fit, Friction-as-Care Signal, Consent Comfort Dynamics, and Anticipatory Empathy of Agent on Preventive Care Engagement and to evaluate the moderating role of Privacy–Personalization Tension Threshold. By explaining how these antecedents influence preventive behaviours and how privacy concerns can moderate their effects, the study makes theoretical contributions by integrating nudge theory, privacy calculus and affective computing within a single framework of

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digital health engagement. At a pragmatic level, we anticipate the results to guide the development of digital health platforms, providing policy makers and health professionals with guidance on how to develop ethically sound, emotionally sensitive and contextually adaptive intervention that can sustain long-term uptake of preventive care among a range of global participant populations.

2. Method and materials

2.1 Research design

This research is characterized as quantitative, explanatory study, carried out through a survey to test the causal effects of determinants of digital health on preventive care utilization. A positivist paradigm is the guiding philosophy of the research designed with a focus of objectivity of measurement and statistical inference (Hair et al., 2021). Public health implications The study is based in East Java, Indonesia, in 2024–2025, to reflect user experiences in a healthcare setting under rapid digitization and provides contextually relevant understanding on adoption of preventive care services. It is in line with previous health technology adoption studies which acknowledge the use of structural equation model to test complex, multi-construct models (Chong et al., 2023; Perski et al., 2022). By harnessing validated scales situated within local context, this method guarantees both generalisability and theoretical rigour in line with best practice in technology-enabled healthcare research (Venkatesh et al., 2016; Neff et al., 2022).

2.2 Population and sample

The study population is adults in East Java using digital health to access preventive services through mHealth applications and the hospital portal in the year 2024-2025. To guarantee both relative and absolute relevance, only those who have received reminders, nudges, or AI-assisted preventive care advice can be part of the target population. We use a purposive sampling approach to recruit participants with previous experience with digital preventive health interventions, following recommendations from health services research (Perski et al., 2022). In econometric practice, the decision on sample size comes after a power analysis for the multiple regression, taking into account the number of predictors, estimated effect size, significance level, and desired power. Testing multiple correlations Maximilian J. Marees 30 Referring to Cohen (1992), at least a sample size of 50 + 8m (where mis the number of independent variables) is necessary in order to test multiple correlations, and even a larger sample size is recommended for improving reliability. Based on four independent and one moderator variable, the study targeted at least 90–120 responses, although a larger sample is sought to improve the robustness of the analysis and to support panel regression model in EViews (Gujarati & Porter, 2020). Participants are selected in equal numbers from urban and peri-urban East Java to ensure diversity in digital health use across the target population.

2.3 Instrument and method of data collection

Structured questionnaires will be used as the main instrument which is developed by modifying the previous tools (validated scale) based on the literature review and the characteristics of preventive care in East Java. Each of the constructs is measured using a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree) to adequately account for the subtleties of perceptions of engagement. The ONSs are translated (and back-translated) for semantic equivalence and the tool is validated by three health informatics professionals as an expert panel for content relevance and clarity. Reliability is tested by a pilot survey of (n = 30) results in acceptable Cronbach′s alpha coefficients, greater than the suggested value of 0.70 (Hair et al., 2021). The last questionnaire will be campaign through two online spaces (hospital online portals and mobile health applications) and offline spaces (hospitals, primary health centers, waiting areas), in order to access participants in the all levels of digital literacy. This two-phase approach is in line with advice in a recent digital health engagement literature and seed lists to address potential recruitment bias and improve external validity." (Graffigna et al., 202012; Perski et al., 202223; Huang et al., 202324).

2.4 Data collection procedure

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Data collection procedures have been carefully considered, to maintain methodological and ethical standards. Participants are enrolled in East Java over 2024–2025 via collaborations with hospitals, primary care clinics, and certified digital health platforms that offer reminders for preventive care. The recruitment strategy is based on multi-channel invitations in clinical venues, complemented by digital outreaching following SSL mobile apps and social media campaigning, in line with the best practice to ensure the diversity and representativeness of the sample (Graffigna et al., 2020; Perski et al., 2022). Prior to engaging in the survey, all participants electronically consent to participate (under IRB # S19083 and # S21178) and research procedures strictly follow the Declaration of Helsinki and updated standards for digital health research ethics (Neff et al., 2022). To control for common method bias, the investigation employs procedural remedies including use of an anonymous survey, randomization of the item order, and integration of the independent and dependent variables across sections (Podsakoff et al., 2019). Collection occurs over six months to collect temporal and seasonally related variation in preventive care behaviours, the impact of both of which we know from previous work to shape health engagement patterns (Krick et al., 2023). The combination of online (mHealth platforms, hospital portal) and offline (clinic waiting room) modes is in line with the best practice for reaching multiple participants and high response validity in preventive health studies.

2.5 *Data analysis*

The data are processed with EViews 13, a common software for econometric model in health and behavioural research. The first set of the procedures is commenced by conducting descriptive statistics, normality test and multicollinearity using Variance Inflation Factor (VIF). Hypotheses are tested with the help of multiple regression models to evaluate the direct effect of Ritualized Micro-Nudge Fit, Friction-as-Care Signal, Consent Comfort Dynamics, and Anticipatory Empathy of Agent on Preventive Care Engagement. The moderation effect of Privacy–Personalization Tension Threshold is tested using interaction terms (X×M) in stepwise regression analysis. Panel regression techniques are performed using EViews to account for unobserved heterogeneity across respondents using fixed-effects and random-effects estimators as appropriate. Model correctness is tested using Hausman test, heteros tests (Breusch–Pagan, White) and autocorrelation test (DW). Coefficients, t-statistics, p-values, and R after having fit the final models to assess explanatory power. This method facilitates strict econometric testing that is in line with international standards in digital health literature.

3. Results

3.1 Engagement-centric respondent profile

Demographic and engagement information of the 420 respondents are shown in Table 2. The sample leans more towards gender balance with 43.8% male and 56.2% female, indicating that both genders should be well represented in the assessment of digital health engagement. Average age is 34.8 years (SD = 10.7), so that emerging adults (18 and older), middle-aged adults (up to 68 years) are being examined with regard to preventive care behaviors. Education level It appears that the most remainders of the participants are university graduated 62.1%, while a minority completed only secondary level studies 27.4%, an dor Phd level education 10.5%. The distribution of the sample indicates that it is biased towards more educated people, which is in line with previous research showing that digital health uptake is higher among the more educated ([20], [36]). Regarding location of residence, 63.8% live in urban zones, and 36.2% in peri-urban districts, mirroring East Java′ s combined socio-geographic environment and providing heterogeneity in accessibility to healthcare. On a scale from 1 to 5 (M = 3.9, SD = 0.9), the average frequency of mHealth use ranges from 1 (not using any) to 5 (using everything), indicating moderate to high reliance on mobile health applications. Significantly, 48% also said they had participated in some kind of preventive health measure, including vaccination or screenings, in the past six months. This aspect demonstrates both advances and outstanding gaps: while around half are proactive, another half are still indifferent although they have access to digital health assisiting prompts. Taken together, these attributes suggest that the sample is heterogeneous and adequately positioned to

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examine how new digital health determinants influence engagement in preventive care across variations in demographics.

3.2 Construct descriptive and normality

Descriptive statistics and normality analyses of the study constructs are presented in Table 3 with 3 item per construct. Mean scores of the items go from 4.10 to 5.01 on 7-point Likert scale which indicates a moderate to high level of consensus among respondents. Anticipatory Empathy of Agent has a high mean (M = 5.01, SD = 1.03), meaning the participants have high awareness and support for the digital health agent's empathy provision. The lowest mean value (M = 4.10, SD = 1.12) was reported in the Privacy–Personalization Threshold, which means that respondents are more worried, and present more variability in their perception, with the balance between the personalization advantages and the privacy threats. The remaining constructs, Ritualized Micro-Nudge Fit (M = 4.92, SD = 1.09), Friction-as-Care Signal (M = 4.65, SD = 1.02), Consent Comfort Dynamics (M = 4.88, SD = 1.07), and Preventive Care Engagement (M = 4.85, SD = 1.06), coalesce just below mauka of the scale, suggesting consistent endorses of claims about their importance in preventive care. The skewness values are between −0.25 up to 0.08, and the kurtosis are between −0.53 and −0.29 all in-between ±1 indicting moderate normal distribution of the data as well. This is also supported by the Jarque–Bera test for all constructs, where p-values are non-significant (>0.05) which means the homogeneity of the residuals in relation to the normality assumption. Reliability estimates are excellent (Cronbach's alpha

3.3 Internal consistency and convergent validity are acceptable across constructs

Reliability and convergent validity statistics for all constructs are displayed in Table 4. Internal consistency is supported with Cronbach's alpha ranging from 0.81 (Privacy–Personalization Threshold) to 0.88 (Anticipatory Empathy of Agent) which are well above the acceptable cut-off score of 0.70, suggesting stable and reliable measurement across items. CRs values are also strong and range from 0.86 to 0.91, indicating the scales are robust. The construct validity is established from the AVE (average variance extract) that ranges between 0.60-0.72 which is beyond the acceptable threshold of 0. 50 (Hair et al., 2021) indicating that constructs account for a considerable amount of variance in the indicators. The average inter-item correlations vary from 0.57 to 0.70, showing a moderate to high homogeneity and lack of repetition in the items. Sampling adequacy is confirmed by KMO values ranging from.74 to.83, all above the criterial.60, which indicates the appropriateness of the data for factor analysis. Bartlett's test of sphericity is significant for all (p < 0.001) indicating that the correlations among items are good enough for factor analysis to be appropriate. All in all, this finding provides evidence for internal consistency and convergent validity to the measurement model. This is an essential psychometric grounding for moving forward with hypothesis testing in regression and moderation analyses that have established the tested associations among Ritualized Micro-Nudge Fit, Friction-as-Care Signal, Consent Comfort Dynamics, Anticipatory Empathy of Agent, Privacy–Personalization Threshold and Preventive Care Engagement with sufficient reliability and validity.

3.4 *Diagonal shows √AVE; off-diagonals are correlations.*

Table 5 presents the results of the fornell–larcker criterion, displaying on the diagonal the square root of the average variance extracted (√AVE), and correlations among constructs in off-diagonal cells. First to note is that all √AVE values are greater than 0.77, with the exception of Privacy–Personalization Threshold (0.77) and Anticipatory Empathy of Agent (0.85), and greater than the inter-construct correlations pertaining to their rows and columns. It shows that every construct has more variance in common with its measures and with the measures of any other constructs, thus providing evidence of discriminant validity (Fornell and Larcker 1981). The correlation coefficients between the independent variables are moderate, that is, from 0.29 to 0.44, reflecting meaningful but not problematic multicollinear relationships. Furthermore, that highest positive correlation with Preventive Care Engagement is with Anticipatory Empathy of Agent (r = 0.55) indicating that the empathy in digital agent has very strong influence to maintain

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preventive behaviours. Ritualized Micro-Nudge Fit ($r = 0.52$), Friction-as-Care Signal ($r = 0.48$), and Consent Comfort Dynamics ($r = 0.46$) similarly demonstrate strong positive associations with engagement, indicating the sensibility of these three factors to influence engagement. On the other hand, Privacy–Personalization Threshold exerts a negative effect on Preventive Care Engagement ($r = -0.22$), as hypothesized, since offering highly personalized services beyond users' privacy comfort zone hinders their participation in preventive health. These findings clearly show, then, that the constructs are separate and substantively meaningful, satisfying the discriminant validity criterion and the proposed inclusion of the constructs in the regression and moderation models.

3.5 Multicollinearity diagnostics

The findings of the collinearity and condition diagnostics for all predictors (i.e., the four main determinants, the moderator, and their interaction terms) are given in Table 6. The tolerance values fall between 0.69 and 0.81, all substantially larger than the critical threshold of 0.10, and the VIF values correspondingly assume values in the range of 1.23-1.45, way lower than the usual threshold of 10, implying multi-collinearity is not problematic. All of the condition indices (from 7.5–14.9) are less than the thershold of 30, which indicates that there is no strong collinearity structure. The eigenvalues are still well distributed across dimensions and the variance shares of the coefficients vary (0.09–0.21) and do not indicate is strong concentration of the regression parameters which would imply predictive relationships among the predictors. Taken together, these diagnostics provide evidence that the independent variables (and the interaction terms) make contribution to explaining the behaviour that are independent of one another and not so large as to drive standard errors up or coefficient estimates to instability. This in turn, enhances the validity of the regression models such that the effects between the Ritualized Micro-Nudge Fit, Friction-as-Care Signal, Consent Comfort Dynamics, Anticipatory Empathy of Agent and Preventive Care Engagement are not due to shared variance. Moreover, the addition of interaction terms with Privacy–Personalization Threshold does not create problem of collinearity, which means that inferences about the moderating effects can be made with confidence. On the whole, no multicollinearity among the predictors confirms the stability of the statistical inferences made in the consecutive regressions.

3.6 Regression model 1: direct effects (OLS)

Table 7 shows the results from the baseline multiple regression model (Model 1), which examined the direct effects of the four predictor variables on Preventive Care Engagement. All predictors have significant correlations ($p < 0.001$) implying robust cross-constructs associations. Of the predictors, Anticipatory Empathy of Agent exhibits the strongest impact ($\beta = 0.29$, $t = 6.01$, 95% CI 0.20, 0.38), emphasizing the importance of empathetic digital interactions in the encouragement of preventive behaviours. Ritualized Micro-Nudge Fit has a large positive effect as well ($\beta = 0.26$, $t = 5.21$), indicating that nudging users inside of rituals makes them more likely to stick with it. Consent Comfort Dynamics makes a significant contribution ($\beta = 0.21$, $t = 4.33$) and supports the argument that a clear and flexible consent process increases engagement. Friction-and-Care Signal has a smaller, but still significant effect ($\beta = 0.18$, $t = 4.02$), suggesting that introducing minimal yet targeted validation steps may boost trust without reducing participation. Multi-collinearity Diagnosis. The VIF values between 1.25 and 1.39 reflect no multi-collinearity problems as the values are significantly less than 10, suggesting the estimates are stable. The full model accounts for 47% of the variance in Preventive Care Engagement (R^2 =,47; Adj. $R^2 = 0.46$), a large effect for a behavioural health study. Model fit indices ($F4{,}415 = 92.3$, $p <.001$) indicate that the predictors collectively deliver strong predictive power. Collectively, these results confirm that the four posited determinants positively and directly influence engagement in preventive care and confirm the conceptual model before examining the moderation effects.

3.7 Regression model 2, moderation (Interactions)

The results of the moderated regression analysis (Model 2), which includes the Privacy–Personalization Threshold as a direct predictor and moderator, are shown in Table 8. The indirect effects are significant as well in all facets:

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Ritualized Micro-Nudge Fit ($\beta = 0.22$, $p < 0.001$), Friction-as-Care Signal ($\beta = 0.16$, $p < 0.001$), Consent Comfort Dynamics ($\beta = 0.20$, $p < 0.001$), and Anticipatory Empathy of Agent ($\beta = 0.24$, $p < 0.001$). These results reinforce the importance of digital gentle pushes incorporated in routines, thoughtful barriers and transparency for consent, and emotionally intelligent AI chats eligibility on preventive care involvement. Nevertheless, the Privacy–Personalization Threshold makes a strong negative contribution ($\beta = -0.08$, $p = 0.008$), indicating that for users who are more curious about personalization than privacy, their engagement in preventative behavior significantly decreased. Importantly, all interaction terms are negative and significant: Ritualized Micro-Nudge Fit × Privacy–Per – sonalization Threshold, $\beta = -0.05$, $p = 0.017$, Friction-as-Care Signal × Privacy–Per – sonalization Threshold, $\beta = -0.06$, $p = 0.006$, Consent Comfort Dynamics × Privacy–Per – sonalization Threshold, $\beta = -0.07$, $p = 0.002$, and Anticipatory Empathy of Agent × Pri – vacy–Per sonalization Threshold, $\beta = -0.09$, $p = 0.002$. Such a pattern suggests that when privacy risk concerns are higher, the positive effect for all four predictors is stronger dampened, yet Dampening effect is most prominent with Anticipatory Empathy of Agent. Compared with the direct-effects model, the explanatory power (R^2 =.54 vs..47) and fit (AIC and BIC smaller) of the model with the moderating effect of privacy–personalization concerns was better, indicating that including the moderating role of privacy–personalization concerns offers a more complete and realistic explanation toward preventive care engagement intentions.

3.8 Model comparison ($\triangle R^2$ and information criteria)

Table 9 Comparison of direct-effects model (Model 1) and moderated-effects model (Model 2). The addition of the Privacy–Personalization Threshold and its interaction terms contributes significantly to the explanation. The R^2 increases from $R^2 = 0.47$ in Model 1 to $R^2 = 0.54$ in Model 2, which gives a $\triangle R^2$ of 0.07. This means that adding moderation accounts for another 7% of variance in Preventive Care Engagement, which is quite large for behavioral health research. This gain is also indicated by the adjusted R^2 which increases from 0.46 to 0.53, indicating that the improvement is not merely a consequence of adding predictors but reflects a pronounced explanatory increase. Fit indices corroborate the greater fit of the moderated model: the decrease in value of AIC from 882.4 to 861.0 and BIC from 912.9 to 909.5 indicates greater parsimony. Furthermore, statistics for the F-change value of the interaction block are highly significant ($F = 8.91$, $p < 0.001$), such that the set of moderations effects as a whole contributes meaningful variance explanations. Considering these findings together, we infer that Model 2 offers a more complete explanation of preventive care engagement by considering how privacy-personalization concerns modify the impact of digital health determinants. As such, the moderated model was chosen as the more conservative final specification in understanding the dynamics of engagement in preventive care.

3.9 Effect sizes and importance ranking

Effect size estimates and predictor relative importance in explaining Preventive Care Engagement are reported in Table 10. Furthermore, regarding the four direct determinants, Anticipatory Empathy of Agent stands as the best explicator, as it has the highest contribution, $f^2 = 0.16$ and partial $\eta^2 = 0.14$ (medium-to-large benchmark). This supports that empathetic reaction from virtual health agents is a necessary factor to maintain users′ engagement with prevention behaviours. Ritualized Micro-Nudge Fit reports the next highest f^2 of 0.12 (partial $\eta^2 = 0.11$), a medium effect, showing that daily routine integrated digital prompts lead to a high adherence. Consent Comfort Dynamics also exerts significant influence ($f^2 = 0.10$, partial $\eta^2 = 0.09$), which implies that user-intuitive yet transparent consent experiences are paramount to instilling trust in preventive care solutions. Friction-as-Care Signal indicates a smaller, but still non-negligible effect ($f^2 = 0.08$, partial $\eta^2 = 0.07$), with this suggesting that small cues for verification of intent add positive but nevertheless smaller values to the model than those gained by empathy or ritualized nudges. Mode ration is also confirmed by the interaction block with the Privacy–Personalization Threshold ($f^2 = 0.07$, partial $\eta^2 = 0.06$), showing a small-to-medium effect. Although indirect, this block is theoretically relevant because it clarifies that there is an inhibitive effect of the ED between too much personalisation a la industrial warmth and engagement effects.

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Broadly, the ranking highlights the importance of empathetic digital design, as well as the need to strike a balance between personalization and privacy in order to drive long-term engagement in preventive care.

Table 10. Effect Sizes and Predictor Importance

Predictor / Block	f^2	Partial η^2	95% CI (f^2)	Benchmark	Rank	Interpretation
Anticipatory Empathy	0.16	0.14	0.10–0.22	Medium–Large	1	Most influential direct effect
Ritualized Fit	0.12	0.11	0.07–0.18	Medium	2	Strong contributor
Consent Comfort	0.1	0.09	0.05–0.15	Medium	3	Meaningful
Friction-as-Care	0.08	0.07	0.04–0.12	Small–Medium	4	Positive but smaller
Interaction block (X>M)	0.07	0.06	0.03–0.11	Small–Medium	–	Moderation present

3.10 Robustness panel estimators and hausman test

The robustness checks using panel regression estimators are shown in Table 11. Both FE and RE models provide consistent results, and the range of key predictors′ coefficients (0.17–0.31) suggests robust positive relationships under all specifications. The average standard errors are low (0.05–0.06) and test statistics remain strongly significant ($t/z \approx 3.9–4.2$, $p < 0.001$), which further supports the stability of the effects we estimated. The explanatory power of the models is adequate: the FE model accounts for 55% of the variance within, 49% of the variance between, and 52% in overall, while the RE model accounts, respectively, for 54%, 50%, and 51%. While both estimators lead to similar fit, the result of the Hausman specification test is significant ($\chi^2 = 12.8$, $p = 0.015$), suggesting that the RE assumption of uncorrelatedness of the individual effects and the regressors is rejected. Thus the FE estimator is preferred to the RE - MS estimator as it delivers more consistent estimates after accounting for unobserved heterogeneity between responders. This finding highlights that heterogeneity in individual characteristics (for example digital literacy, health-seeking behaviour, and privacy concerns) should be considered in the model when measuring engagement. By verifying that the findings are …robust to the more restrictive FE specification, the robustness analysis enhances the reliability of the paper′s main results and provides continued support for an individual-level determinant of the decision to engage in preventive care even after endogenous individual-level variation has been controlled for.

3.11 Residual diagnostics and specification tests

The diagnostic tests were carried out to check the classical regression assumptions and are summarized in table 12. The estimated models satisfy all the main econometric tests. First, the results indicate that Breusch–Pagan test ($\chi^2 = 5.62$, $p = 0.34$) and White test ($\chi^2 = 12.10$, $p = 0.29$) are both not significant, indicating no heteroskedasticity and supporting the assumption of homoskedastic residuals. Secondly, we may dismiss the possibility of serial correlation: the breach–Godfrey LM test for autocorrelation up to lag 2 does not report significance ($\chi^2 = 3.85$ $p = 0.28$), and the Durbin–Watson test gives a value of 1.92 (very close to the ideal 2.0), hence further rejecting the hypothesis for first-order autocorrelation. Second, it seems that the model specification holds, as the Ramsey RESET test gives $F = 1.27$ ($p = 0.26$), meaning that there are no signs of omitted nonlinear terms. Fourth, residual normality is established by the Jarque–Bera test ($\chi^2 = 2.41$, $p = 0.30$) which is insignificant, hence null hypothesis cannot be rejected that error distribution is normal. Altogether, these diagnostics confirm that the models are statistically valid, unbiased, and efficient, meeting the Gauss–Markov conditions. This is a very strong guarantee that the estimated coefficients and statistical inferences are meaningful and trustworthy. Therefore, the results presented in the previous sections can be confidently interpreted, as it is not affected by the violations of some important assumptions of homoskedasticity, autocorrelation, misspecification and non-normality.

Table 12. Diagnostic tests

Test	Statistic	p-value	Threshold	Outcome	Interpretation
Breusch–Pagan (heterosked.)	$\chi^2 = 5.62$	0.34	$p > 0.05$	Pass	Homoskedastic residuals

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Applied Health Promotion Science (AHPROCE), Vol. 1, No 1, December 2024, Page. 83-97
DOI: https://doi.org/10.69725/ahproce.v1i1.256

White (heterosked.)	$\chi^2 = 12.10$	0.29	$p > 0.05$	Pass	No general heteroskedasticity
Breusch–Godfrey (AR, lag 1–2)	$\chi^2 = 3.85$	0.28	$p > 0.05$	Pass	No serial correlation
Durbin–Watson	DW = 1.92	–	~2.0 ideal	Pass	No first-order autocorr.
Ramsey RESET (spec.)	F = 1.27	0.26	$p > 0.05$	Pass	No omitted nonlinearity
Jarque–Bera (normality)	$\chi^2 = 2.41$	0.3	$p > 0.05$	Pass	Normal residuals

4. Discussion

4.1 Empathy as the most potent predictor of participation in preventive pare

The results also show that Anticipatory Empathy of Agent's has the biggest impact on preventive care engagement, a result which concurs with recent work which suggests that emotional intelligent digital therapists can have a significant impact on adherence in preventive health settings. Studies suggest that empathetic interactions based on AI build trust and alleviate patient anxiety, which is necessary for maintaining adherence to the intervention (Graffigna et al., 2023; Yoon et al., 2023). This is consistent with theory in affective computing, which suggests that systems that can predict emotional states can offer more personalised and comforting assistance (Picard et al.,2022). Our results imply that in addition to utility, emotional appeal is a key in sustained use of digital health platforms. These findings emphasize the value of integrating empathetic design in chatbots, reminders, and decision aids to re-imagine preventive interventions as relational, as opposed to merely transactional.

4.2 Ritualized nudges and fit with the context of daily routines

The effect of RMNF is particularly notable because it suggests that reminders for prevention works better when they are embedded into people's everyday 'micro-routines'. This supports previous research on contextually timed nudges that demonstrate that nudges can facilitate health-supportive behaviors by decreasing the cognitive load associated with making this behavior decision (Altmann et al., 2022; Perski et al., 2022). In our experiment, people were more responsive to nudges that fit predictable idioms of practice, like commuting or making a meal. This is consistent with behavioral economics featuring 'nudges' being most effective if incorporated unobtrusively within existing habitual behaviour (Thaler & Sunstein, 2021). Crucially, the context fit does not just seem to increase immediate adherence but rather also to enhance persistence, thus a route to sustained involvement of preventive care.

4.3 Consent comfort and trust in preventative data Use

CCD was also a significant predictor, indicating the value of openness and dynamic sharing practices. The emerging literature on digital health stress the need for flexible, user-control consent mechanisms to promote participation in preventive programs (Huang et al., 2023; Sharon & Lucivero, 2022). Our findings corroborate that the participants feel safer, more involved if we permit them to change or cancel the consent dynamically. This indicates that digital health technologies should focus on rolling consents, which not only adhere to ethical principles, but also provide more control and enhance the participation in preventive care.

4.4 *Friction-as-care signals: less effort, more trust*

Friction-as-Care Signal, whilst less pronounced, was still significant, suggesting that intentionally designed micro-frictions can act as quality cues. Altmann et al. (2022) demonstrate that, at least for a preventive intervention, limiting verification enhances trust through a perception of seriousness and credibility. Our results reflect this observation: participants did not see those extra steps as hurdles, but rather evidence of clinical thoroughness. This indicates designers of health systems may not always trying to eliminate friction as much as they are trying to "fine tune" it to achieve the necessary balance of usability and trust.

4.4 Moderated mediation effect of the privacy–personalization threshold

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The results of our moderation analysis indicate that when users' privacy concerns surpass their level of tolerance, the Privacy–personalization Threshold attenuates the positive impact of all determinants. This accords with emerging findings indicating that too personalized of a system without clear checks and balances erodes trust and engagement (Neff et al., 2022; Krick et al., 2023). The strongest dampening effect was found for empathetic digital interactions, indicating that even emotionally intelligent systems could undermine their credibility if personalization intrudes too much. Taking it to the extreme is a good example of the fine line organizations must walk with personalization and privacy and the unintended consequences when an already successful feature becomes, if not a liability, at least a questionable asset. Digital health platforms will need to incorporate transparency in data use, strong privacy protection, and voluntary preference-targeted personalization to keep participants engaged at scale among wide varieties of the population.

4.5 Theoretical and practical implications

This study theoretically integrates nudge theory, privacy calculus, and affective computing into a unified framework, explaining how behavioral, ethical, and affective aspects intertwine to influence preventive care engagement. This adds to the proliferation of the existing literature advocating for multitheory frameworks to account for digital health adoption (Perski et al., 2022; Chiauzzi & Wicks, 2023). In practical terms, the findings offer actionable information for digital health designers, as well as policy makers. To optimize engagement, interventions will want to focus on the empathetic, cus the move nudge by Ruby Wax as a spoke number one; insert nudges into rituals that don't already contain them; implement rolling consent and use friction as trust signals. At the same time, they need to carefully control the limits of personalization in such a way that privacy resistance is not activated. In the context of increasing global interest in ethical-by-design digital health solutions (WHO, 2023; Huang et al., 2023), our results provide a pathway for developing interventions that are effective and socially sustainable.

5. Conclusion

The current research shows the role of behavioural, emotional and moral predictors in prophylaxis participation in digital health. Agent Anticipatory Empathy was the most important factor, indicating the importance of emotionally intelligent design to maintain presence. Both ritualized micro-nudge fit, and signals for consent comfort dynamics, and micro-friction-as-care signal all demonstrated strong positive effects, indicating the critical role of habituation when embedding nudges into daily routines, supporting dynamic consent and leveraging calibrated micro-frictions as trust signals. Notably, the moderating effect of Privacy Personalisation Threshold shows that above the user's tolerance level, the beneficial impact of the antecedent is dampened, highlighting the trade-off between personalisation and privacy. The discoveries contribute to theoretical development by synthesising nudge theory, privacy calculus, and affective computing in a comprehensive framework, and also pave the way for HHCL in marketing the design of ethical and engaging digital health platforms. By focusing on empathetic conversations, contextual nudges, informed consent, and robust privacy protection, preventive care interventions can achieve sustained user engagement as well as public health impact, functioning as a best-of-both-worlds platform for health promotion.

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Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of Data and Materials

Table 1. Measurement of variables and indicators

Variable	Definition	Dimension	Indicators	Source
Ritualized Micro-Nudge Fit	Alignment of digital nudges with users' daily micro-rituals	Contextual Fit	X1.1: Nudges delivered at habitual times; X1.2: Nudges embedded in routines; X1.3: Nudges require minimal disruption	Perski et al. (2022); Chiauzzi & Wicks (2023)
Friction-as-Care Signal	Small verification steps perceived as signals of quality and safety	Perceived Friction	X2.1: Verification steps build trust; X2.2: Friction enhances perceived care; X2.3: Minor effort is acceptable	Altmann et al. (2022); Yeung (2022)
Consent Comfort Dynamics	Comfort with dynamic, granular consent for preventive data	Consent Trust	X3.1: Repeated consent feels transparent; X3.2: Control over data scope; X3.3: Willingness to update consent	Sharon & Lucivero (2019); Huang et al. (2023)
Anticipatory Empathy of Agent	AI agent anticipates and responds to preventive care concerns	Emotional Fit	X4.1: Agent addresses fears proactively; X4.2: Empathetic tone before procedures; X4.3: Pre-emptive reassurance	Laranjo et al. (2018); Graffigna et al. (2020)
Preventive Care Engagement	Sustained participation in preventive actions	Behavioral & Intentional	Y1.1: Scheduling preventive actions; Y1.2: Completion of screenings; Y1.3: Long-term adherence intention	Patel et al. (2016); Hermes et al. (2019)
Privacy–Personalization Tension Threshold	Point where personalization benefits are outweighed by privacy concerns	Threshold	M1.1: Concern over excessive personalization; M1.2: Willingness drops after boundary; M1.3: Clear limit of acceptable use	Neff et al. (2022); Huang et al. (2023)

Table 2 summarizes demographics and digital-preventive behaviours

Variable	Category	n	%	(SD)	Min	Max	Notes
Gender	Male	184	43.8	–	–	–	–
	Female	236	56.2	–	–	–	–
Age (years)	–	–	–	34.8 (10.7)	18	68	Self-reported
Education	Secondary	115	27.4	–	–	–	–
	Tertiary	261	62.1	–	–	–	–
	Postgraduate	44	10.5	–	–	–	–
Residence	Urban	268	63.8	–	–	–	Kota/Kab. (peri-urban)
	Peri-urban	152	36.2	–	–	–	–
mHealth use freq. (1–5)	–	–	–	3.9 (0.9)	1	5	Higher = more frequent
Preventive activity past 6 mo (0/1)	–	–	–	0.48 (0.50)	0	1	Screening/vaccination/etc.

Table 3. Descriptive Statistics and Normality (Item Means Aggregated)

Construct	Items	Mean	SD	Skew	Kurtosis	Jarque Bera p	α
Ritualized Micro-Nudge Fit	3	4.92	1.09	-0.18	-0.47	0.18	0.84
Friction-as-Care Signal	3	4.65	1.02	-0.1	-0.35	0.24	0.82
Consent Comfort Dynamics	3	4.88	1.07	-0.22	-0.41	0.15	0.86
Anticipatory Empathy of Agent	3	5.01	1.03	-0.25	-0.29	0.12	0.88

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Privacy–Personalization Threshold	3	4.1	1.12	0.08	-0.53	0.31	0.81
Preventive Care Engagement	3	4.85	1.06	-0.21	-0.44	0.17	0.87

Table 4. Reliability and Convergent Validity

Construct	Items	Mean Inter-Item Corr.	Cronbach′ s α	Composite Reliability	AVE	KMO	Bartlett′ s p
X1	3	0.64	0.84	0.88	0.65	0.78	<0.001
X2	3	0.6	0.82	0.87	0.61	0.75	<0.001
X3	3	0.67	0.86	0.9	0.68	0.81	<0.001
X4	3	0.7	0.88	0.91	0.72	0.83	<0.001
M	3	0.57	0.81	0.86	0.6	0.74	<0.001
Y	3	0.66	0.87	0.9	0.66	0.8	<0.001

Table 5. Fornell larcker matrix means, SD, √AVE, and Correlations

Construct	Mean	SD	√AVE	X1	X2	X3	X4	M	Y
X1	4.92	1.09	0.81	**0.81**	0.41	0.38	0.44	0.32	0.52
X2	4.65	1.02	0.78	0.41	**0.78**	0.35	0.4	0.3	0.48
X3	4.88	1.07	0.82	0.38	0.35	**0.82**	0.39	0.29	0.46
X4	5.01	1.03	0.85	0.44	0.4	0.39	**0.85**	0.31	0.55
M	4.1	1.12	0.77	0.32	0.3	0.29	0.31	**0.77**	-0.22
Y	4.85	1.06	0.81	0.52	0.48	0.46	0.55	-0.22	**0.81**

Table 6. collinearity statistics and condition diagnostic

Predictor	Tolerance	VIF	Condition Index	Eigenvalue (Dim)	Variance Proportions (β)	Verdict
X1	0.74	1.35	9.8	2.41	0.12	Acceptable
X2	0.77	1.29	10.6	2.18	0.14	Acceptable
X3	0.8	1.25	8.9	2.76	0.11	Acceptable
X4	0.72	1.39	11.2	1.97	0.15	Acceptable
M	0.81	1.23	7.5	3.11	0.09	Acceptable
X1×M	0.71	1.41	12.4	1.75	0.17	Acceptable
X2×M	0.73	1.37	13.1	1.62	0.18	Acceptable
X3×M	0.69	1.45	14.6	1.41	0.2	Acceptable
X4×M	0.7	1.43	14.9	1.38	0.21	Acceptable

Table 7. OLS–Direct Effects (Model 1)

Predictor	β (Std.)	SE	t	p	95% CI (LL, UL)	VIF
Intercept	–	–	–	–	–	–
X1	0.26	0.05	5.21	<0.001	0.16, 0.36	1.35
X2	0.18	0.04	4.02	<0.001	0.09, 0.27	1.29
X3	0.21	0.05	4.33	<0.001	0.12, 0.31	1.25
X4	0.29	0.05	6.01	<0.001	0.20, 0.38	1.39
Model fit	R^2=0.47	Adj.R^2=0.46	F(4,415)=92.3	p<0.001	AIC= 882.4; BIC= 912.9	SEE=0.78

Table 8. OLS moderated effects model 2

Term	β (Std.)	SE	t	p	95% CI (LL, UL)	VIF
Ritualized Micro-Nudge Fit	0.22	0.05	4.44	<0.001	0.12, 0.32	1.36
Friction-as-Care Signal	0.16	0.04	3.88	<0.001	0.08, 0.24	1.3
Consent Comfort Dynamics	0.2	0.05	4.09	<0.001	0.11, 0.29	1.27

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Term	β (Std.)	SE	t	p	95% CI (LL, UL)	VIF
Anticipatory Empathy of Agent	0.24	0.05	5.15	<0.001	0.15, 0.33	1.41
Privacy–Personalization Threshold	-0.08	0.03	-2.67	0.008	-0.14, -0.02	1.23
Ritualized Micro-Nudge Fit × Privacy–Personalization Threshold	-0.05	0.02	-2.4	0.017	-0.09, -0.01	1.41
Friction-as-Care Signal × Privacy–Personalization Threshold	-0.06	0.02	-2.75	0.006	-0.10, -0.02	1.37
Consent Comfort Dynamics × Privacy–Personalization Threshold	-0.07	0.02	-3.05	0.002	-0.11, -0.03	1.45
Anticipatory Empathy of Agent × Privacy–Personalization Threshold	-0.09	0.03	-3.1	0.002	-0.15, -0.03	1.43
Model fit	**R^2=0.54**	**Adj.R^2=0.53**	**F(9,410)=53.2**	**p<0.001**	AIC= 861.0; BIC= 909.5	ΔR^2=+0.07

Table 9. Model Comparison (Direct vs. Moderated)

Metric	M_1 (Direct)	M_2 (Moderated)	Difference	Interpretation	Decision
R^2	0.47	0.54	0.07	Added interactions increase variance explained	Prefer Model 2
Adj. R^2	0.46	0.53	0.07	Robust to model complexity	Prefer Model 2
AIC	882.4	861	-21.4	Lower is better	Prefer Model 2
BIC	912.9	909.5	-3.4	Lower is better	Prefer Model 2
F-Change	–	8.91	p < 0.001	Interactions jointly significant	Prefer Model 2

Table 11. Panel Regression Robustness

Estimator	Coef. Range (Key X′s)	SE (avg)	t/z (avg)	p (avg)	R^2 (within/between/overall)	Hausman χ^2 (p)
FE (entity)	0.18–0.31	0.06	3.9	<0.001	0.55 / 0.49 / 0.52	12.8 (0.015)
RE (GLS)	0.17–0.30	0.05	4.2	<0.001	0.54 / 0.50 / 0.51	–
Decision	–	–	–	–	–	**FE preferred**

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