

Enhancing Menstrual Health Research through User-Centred Digital Data Structures: Findings from a Researcher Needs Study

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Abstract: Progress in diagnosis, treatment, and health equity has been hampered by persistent gaps in women's health research, especially in the field of menstrual health. Digital menstrual cycle tracking apps (MCTAs) provide an opportunity to fill these gaps by offering extensive, user-generated data. This ongoing study aims to identify the needs of researchers and medical professionals regarding the collection and integration of menstrual health-related data in research and practice, to suggest a research-ready, ethical data structure for research MCTAs. A digital survey was distributed to over 500 experts, yielding 127 responses across clinical, behavioural science, and digital health domains. Respondents rated menstrual, sociodemographic, reproductive, stress, sleep, psychological, and nutrition data as highly relevant, and preferred self-report for subjective domains and passive tracking for physiological measures. Clinical data (such as endocrine biomarkers or gynecological examination results) were rated as highly burdensome to collect and integrate, indicating the need for layered consent, opt-in, and a privacy-protective design. Based on these findings, a three-tiered data structure: core, optional, and sensitive layers, was proposed to balance research utility with user autonomy and privacy. Preliminary results offer guidance for developing research-ready MCTAs.


1 INTRODUCTION


Women's health, especially menstrual health, remains significantly underrepresented in biomedical research, contributing to diagnostic delays, mismanagement of chronic conditions, and persistent inequities (Peters & Woodward, 2023; National Institutes of Health, 2023). The disparities in women's health research are evident in funding. Although diseases like endometriosis affect roughly 10% of women worldwide and go undiagnosed for an average of 7–10 years, women's health research has historically been deprioritised, and less than 2% of medical research funding is spent on pregnancy, childbirth and female reproductive health (World Economic Forum, 2024; National Academies of Sciences, 2024). Another report indicated that diseases that disproportionately affect women, including endometriosis, migraine,

headaches, and anxiety disorders, receive much less funding relative to the burden they pose on the U.S. population (Smith, 2023). In the U.K., less than 2.5% of publicly funded research is dedicated solely to women's reproductive health (U.K. Clinical Research Collaboration, 2025), even though a survey of 7,367 women conducted by Public Health England (PHE) (2018) revealed that 31% of this population experienced severe reproductive health symptoms such as heavy menstrual bleeding, menopause, incontinence, and infertility in the last 12 month.

Digital menstrual cycle tracking applications (MCTAs) present an opportunity to close this gap by enabling large-scale, user-generated, longitudinal data collection (Schantz et al., 2021). More than 50 million women worldwide use such applications (Kelly & Habib, 2023), and evidence indicates that

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cycle tracking data can support improved clinical decision-making in conditions such as endometriosis, PCOS, infertility, and perimenopause (Hohmann-Marriott et al., 2023). Electronic tracking of conditions like premenstrual syndrome, migraines, or iron deficiency may improve patient outcomes by associating symptoms with specific menstrual phases (Petrušić et al., 2024)

Despite this potential, existing MCTAs often lack research-ready architectures, standardised data models, ethical safeguards, and interoperability with clinical systems (Principe et al., 2024; Sou et al., 2024). One study conducted in the U.K. found that the Flo period app, which has over 1.5 million female users, did not provide options to log relevant perimenopausal symptoms, such as hot flashes, night sweats, brain fog, etc (Cunningham et al., 2024). Beyond gaps in symptom coverage, the Flo app has also been criticised for limited data governance features, most notably the inability for users to export or port their data (Privacy International, 2025). This limitation restricts users' autonomy, prevents meaningful participation in research, and hinders seamless transitions between apps or data integration across platforms. Most of the existing MCTAs also face criticism due to inadequate data privacy safeguards, with cases of private health information being used for targeted advertising or shared with other parties without the user's consent (Downing & Perakslis, 2022). A majority of the MCTAs are designed for personal tracking rather than research, lacking standardised variables, interoperable data formats, and robust consent models. In addition, they often target younger, menstruating women, neglecting the needs of those in perimenopause or with irregular cycles (Cunningham et al., 2024). Moreover, researchers report difficulty accessing high-quality menstrual and reproductive health data due to fragmented collection methods and variable user engagement (Earle et al., 2021; Health-Americas, T. L. R., 2022). In contrast to other domains where data donation models, such as social media usage studies, have been effectively applied (e.g., data-donation.ch), menstrual health has not yet extensively investigated this strategy.

To address these gaps, this study investigates the following research questions:

(RQ1) What data types, collection preferences, and ethical expectations do researchers and healthcare professionals identify as essential for advancing menstrual and reproductive health research? and

(RQ2) How can these requirements be translated into a user-centred, privacy-preserving data infrastructure that supports research-ready menstrual health tracking?

2 METHODS

2.1 Study Design

To answer our research questions, a mixed-methods, cross-sectional digital survey was developed to collect quantitative and qualitative data from an expert audience. The design was chosen to capture both structured assessments of the perceived relevance and burden of collecting female-specific health data, as well as open-ended reflections on broader requirements for a research-ready menstrual health data infrastructure. The survey was informed by prior design and research work on *CyMe [si:][mi:]*¹, an open-source, research-oriented women's health tracking concept (Principe et al., 2024; Sou et al., 2024). *CyMe* served as a sensitising artefact to structure the identification of relevant data domains, ethical considerations, and potential data collection modalities, rather than as an evaluated or deployed intervention. Insights from this study are intended to inform the continued development of *CyMe* and comparable research-ready menstrual health platforms.

The study involved anonymous, minimal-risk data collection and did not request any identifiable personal information. In accordance with institutional guidelines, the study was formally exempt from ethics review from the IRB of the University of St.Gallen.

2.2 Participant Recruitment and Screening

Both male and female participants were recruited using Prolific's pre-screening filters to target individuals working in healthcare, medicine, or health-related research roles. The inclusion criteria required participants to be at least 18 years old, English-speaking, and currently employed or trained in a health-related professional field. Individuals without relevant professional experience were excluded via Prolific's automated eligibility filters. They were primarily based in the United Kingdom, Germany, and Switzerland, and were compensated in accordance with Prolific's fair-pay guidelines.

¹ *CyMe [si:][mi:]* project website: <https://www.c4dhi.org/projects/cyme-womens-health-research-app/>

2.3 Survey Instrument

The survey was developed in several iterations and drew on existing literature on menstrual cycle tracking and digital health research (Earle et al., 2021; Symul et al., 2019).

Building on a pre-study involving 32 expert participants and a comprehensive literature review of female and menstrual health data, we identified 68 health-related data types, which were organized into eight distinct categories (Appendix A, Table A4): Menstrual Cycle; Symptoms and Physical Health; Reproductive Health; Clinical and Medical Data; Mental Health and Well-being; Lifestyle and Behaviour; Psychosocial Factors; and Societal and Demographic Factors. These data types were selected to reflect a comprehensive yet research-usable representation of variables relevant to female and menstrual health. The selection aimed to include variables that are commonly tracked in existing menstrual and health apps, clinically relevant for diagnosing or monitoring female-specific conditions such as PCOS, endometriosis, or PMDD, and psychologically meaningful for assessing mental health and well-being across the menstrual cycle. In addition, contextually essential factors were considered, including lifestyle behaviours, psychosocial conditions, and societal influences known to affect or modulate menstrual health.

The final questionnaire was structured into seven sections. After providing informed consent and undergoing internal screening, participants were first asked to provide information on their demographic and professional background. They were then introduced to the study topic and the concept of developing a research-ready MCTA.

Eventually, the main section of the survey asked participants to rate the relevance and burden of these 68 predefined health data types structured around 8 data categories using two 4-point Likert scales (1 = very low to 4 = very high). Participants also indicated preferred data-collection modes (self-report vs. passive sensing) and responded to open-ended questions about ethical and design considerations.

The survey was implemented using Limesurvey, hosted on the servers of University of Zurich.

2.4 Data Analysis

Building on the cross-sectional, mixed-methods design outlined in Section 2.1, quantitative responses were analysed using descriptive statistics, while qualitative free-text entries underwent thematic analysis

(Braun & Clarke, 2006). Quantitative analysis involved calculating descriptive statistics (mean, SD) for relevance and burden scores for each data domain. These scores were further plotted to visualise the relevance-burden trade-off, as shown in Figure 2. Qualitative analysis involved thematic coding of open-ended responses to identify key themes related to data needs, challenges, and ethical considerations. Ethical protocols adhered to standard digital research practices, using anonymous participation and one-time outreach (ICC, 2025).

3 RESULTS

3.1 Sample Characteristics

In total, 127 individuals completed the survey (68.4% female, mean age = 40.7 years, SD = 11.5). Most participants were between the ages of 35 and 44 years (33.8%), while the others were between the ages of 25 and 34 years (29.2%) and 45 and 54 years (16.2%).

Overall, 67.7% were trained health care professionals (e.g., physicians, nurses, or allied health professionals), while 32.3% were non-clinical professionals working in the health care sector, including individuals in education, business administration, finance, IT, and R&D. A significant majority (61.7%) held leadership or supervisory positions, indicating high professional seniority among respondents.

3.2 Quantitative Findings

3.2.1 Top 10 Most Relevant Health Data Types

The top 10 most relevant health data types (out of 68) were dominated by affective/cognitive symptoms and societal factors, reinforcing the importance of a holistic, biopsychosocial approach to women's health research (Table 1). These data types were included because menstrual health intersects not only with reproductive physiology but also with mental, cognitive, and social factors that influence overall well-being, making them highly relevant for research-ready MCTAs. As shown in Table 1, "Depressive symptoms" ranked as the most relevant data type with a mean score of 3.33 (SD = 0.92), followed closely by "Anxiety/worry" (M = 3.27, SD = 0.91). Notably, five of the top ten entries fall under the "Affective and Cognitive Symptoms" category, including sleep disturbances, mood swings, and cognitive fog. This strong emphasis reflects a growing recognition of the

interdependence between menstrual cycles and mental health. This association is supported by both clinical and self-tracked data, which demonstrate that hormonal fluctuations throughout the cycle can impact mood, cognition, and emotional regulation.

Table 1: Top 10 Most Relevant Data Types.

Data Category	Data Type	Mean	SD	N
Affective/Cognitive Symptoms	Depressive symptoms	3.33	0.92	91
Affective/Cognitive Symptoms	Anxiety/worry	3.27	0.91	93
Societal Factors	Privacy and trust in data use	3.26	0.96	106
Societal Factors	Intersectionality (socio-economic status, education, migration, disability, race/ethnicity, religion, culture)	3.22	0.96	110
Societal Factors	Access to care	3.21	0.97	111
Affective/Cognitive Symptoms	Sleep disturbances	3.20	0.96	94
Reproductive Status & History	Pregnancies	3.17	0.97	94
Affective/Cognitive Symptoms	Mood swings, emotional sensitivity	3.16	1.01	91
Physical Symptoms	Hot flashes/night sweats	3.11	0.95	90
Affective/Cognitive Symptoms	Cognitive fog/fatigue	3.11	1.03	91

“Societal factors” also feature prominently in the top-rated items, with “Privacy and trust in data use” (M = 3.26, SD = 0.96), “Intersectionality” (M = 3.22, SD = 0.96), and “Access to care” (M = 3.21, SD = 0.97) receiving consistently high relevance ratings. These findings suggest that researchers view the social and structural context, including stigma, discrimination, and accessibility, as integral to the understanding of menstrual and reproductive health. In other words, health data are not interpreted in isolation, but are shaped by the lived realities of individuals, especially those in marginalised groups.

Conversely, Appendix B (Table A5) lists the top 10 least relevant and burdensome data types, highlighting items that researchers considered lower priority for inclusion in research-ready MCTAs. This provides a complementary perspective, showing which physiological or demographic measures may be less critical or less informative in comparison to the most relevant variables.

Table 2: Top 10 Most Burdensome Data Types.

Data Category	Data Type	Mean	SD	N
Societal Factors	Disclosure of sensitive experiences	2.75	1.01	105
Affective/Cognitive Symptoms	Depressive symptoms	2.64	1.02	92
Societal Factors	Privacy and trust in data use	2.59	1.05	107
Societal Factors	Cultural and gender norms	2.57	1.11	103
Societal Factors	Stigma around menstruation/menopause	2.54	0.99	102
Hormonal or Clinical Bio-markers	Anti-Müller-Hormon (AMH)	2.53	1.11	70
Hormonal and Clinical Bio-markers	Menstrual blood biomarkers	2.53	1.13	76
Societal Factors	Intersectionality (socio-economic status, education, migration, disability, race/ethnicity, religion, culture)	2.51	1.03	111
Societal Factors	Family & partner support	2.49	1.03	111
Stress and Recovery Physiology	Calories burned at rest (BMR)	2.48	0.98	75

To reflect this complexity, the survey deliberately included variables beyond purely physiological cycle tracking. Data related to mental health, social context, and basic demographics were included to capture the full spectrum of factors that may interact with menstrual and female health, either as outcomes of hormonal dynamics or as moderators of symptom experience, data quality, and health equity. Top 10 Most Burdensome Health Data Types

While overall relevance was high, experts also acknowledged the challenges associated with collecting certain types of data.

The survey identified the top 10 data types perceived as most burdensome to collect, either for the participant or the researcher. Data types rated as most burdensome (5/5 on a 5-point scale in open-ended responses) included clinical diagnoses, endocrine testing, gynecological exams, and fertility challenges. This high burden reflected privacy sensitivities, stigma, medical complexity, and the emotional labour associated with these domains (Grando et al., 2020; Morgan, 2016). The quantitative ratings, presented in Table 2, show that societal factors are overwhelmingly represented in this list, comprising six of the top ten entries. “Disclosure of sensitive experiences” was rated as the most burdensome data type ($M = 2.75$, $SD = 1.01$), underscoring the ethical and emotional weight of collecting trauma-related or deeply personal information. This is followed by “Depressive symptoms” ($M = 2.64$, $SD = 1.02$), which notably also topped the relevance list, creating a classic relevance-burden dilemma for researchers. The high burden associated with societal factors like “Privacy and trust” ($M = 2.59$, $SD = 1.05$), “Cultural and gender norms” ($M = 2.57$, $SD = 1.11$), and “Stigma around menstruation/menopause” ($M = 2.54$, $SD = 0.99$) highlights the profound difficulty of capturing and quantifying complex social dynamics. Even seemingly objective biomarkers like “Anti-Müller-Hormon (AMH)” ($M = 2.53$, $SD = 1.11$) are considered burdensome, likely due to the cost, invasiveness, and potential for causing anxiety in participants.

To provide a contrasting view, Appendix B (Table A6) provides the top 10 least burdensome data types, indicating which variables were considered easiest to collect by researchers and participants. These least burdensome measures included relatively straightforward physiological or reproductive data, such as appetite changes, acne/skin changes, and cycle start and end dates. Highlighting both the most and least burdensome items offers researchers practical guidance for survey design and prioritisation when balancing data relevance against collection feasibility.

3.2.2 Relevance vs Burden

Analysis of the responses from 127 participants revealed that, overall, health data types were rated as moderately relevant ($M = 2.83$, $SD = 1.05$) and had a relatively low burden ($M = 2.29$, $SD = 1.04$) on a 1–4 scale. Figure 1 presents the distribution of relevance

and burden scores across all rated health data categories. The histogram displays the frequency of ratings, showing how many individual ratings fell into each type on the 1–4 scale. For example, a relevance score of 2 was assigned 20 times across all data items, while a burden score of 2 occurred 30 times. This visualisation highlights that most health data categories were perceived as moderately relevant and generally low to moderate burden, providing a clear overview of participants’ collective judgments.

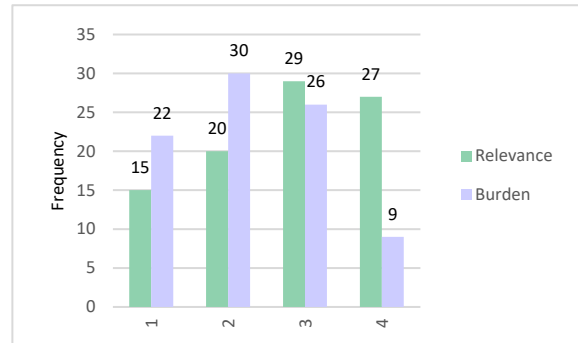


Figure 1: Histogram showing the distribution of relevance and burden scores (1-4 rating).

Correlation analysis indicated a moderate, statistically significant positive relationship between relevance and burden (Pearson $r = 0.309$; Spearman $\rho = 0.289$; both $p < 0.001$). This suggests that questions perceived as more important also tend to be perceived as more burdensome, although the association is far from deterministic.

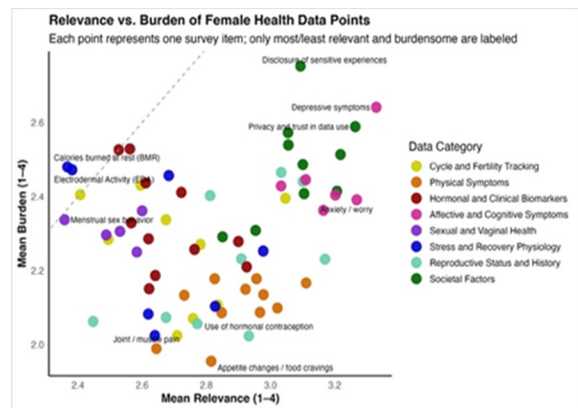


Figure 2: Scatter plot showing relevance vs burden and regression line with 95% confidence interval.

Cross-tabulations revealed that higher relevance levels were associated with higher proportions of responses with medium or high burden. Quadrant analysis using the median cut-offs (relevance ≥ 3 ; burden ≥ 3) showed that responses were almost evenly split

between high relevance/low burden (33.0%) and high relevance/high burden (33.1%).

Low-relevance/low-burden responses comprised 25.8%, while the least desirable combination, low relevance/high burden, accounted for only 8.2%. This distribution highlights both the strength of well-designed high-value, low-effort items and the presence of a small subset of questions that may impose unnecessary burden. Inferential tests reinforced these patterns. A chi-square test confirmed a significant association between relevance and burden categories ($\chi^2 = 1523.13$, $p < 0.0001$), and one-way ANOVA showed that mean burden scores increased significantly across relevance levels ($F(3, 5725) = 234.18$, $p < 0.0001$). Mean burden rose from 1.53 for low-relevance items to 2.55 for high-relevance items, indicating a gradual upward trend rather than a sharp increase.

Overall, the results show that while higher relevance is generally associated with a higher burden, substantial variability exists, with many high-relevance questions being rated as easy. The presence of both optimal (high relevance, low burden) and problematic (low relevance, high burden) items suggests opportunities to refine question design to maximise survey efficiency and respondent experience. Key implications for survey and app-based data collection design include prioritizing items that naturally fall into the high-relevance/low-burden quadrant, simplifying or restructuring high-relevance/high-burden items, and reevaluating low-relevance/high-burden questions for possible removal or redesign. Overall, striking a balance between scientific value and user effort is crucial for maintaining respondent engagement and ensuring the quality, completeness, and usability of menstrual health datasets within digital health research infrastructures.

3.2.3 Data Collection Preferences

Beyond what data to collect, experts expressed clear preferences on how to collect it. The findings reveal a nuanced understanding of the strengths and limitations of various methodologies. Participants prefer self-reported data for subjective domains (e.g., emotions, cognition), context-sensitive data (e.g., substance use, sexual activity), and data that sensors cannot consistently capture (e.g., sociodemographic or psychological status). Age, education, income, psychological well-being, mental health status, sexual activity, preferences, and health are among the most commonly requested sociodemographic data for self-reporting.

Conversely, researchers preferred passive tracking for variables that can be objectively assessed (e.g., vitals, sleep), are susceptible to self-reporting bias (e.g., activity levels), and necessitate continuous or longitudinal monitoring. This dual approach, combining subjective self-reports with objective passive sensing, is seen as the optimal strategy for building a rich, multi-layered dataset that captures the complexity of female health.

3.3 Qualitative Insights: Key Challenges, Awareness and Attitudes

Thematic analysis of open-ended responses highlighted several critical challenges that a research-ready platform must address. One participant noted that there is “*limited availability of large, high-quality, anonymised datasets focused on female-specific health factors*” (P443). Another participant noted that “*female-specific health data is often fragmented, inconsistent or locked inside proprietary platforms that don't share openly. It's also hard to ensure the data reflects diverse experiences, especially for people with irregular cycles or from underrepresented communities*” (P485). Another participant stated that the “*lack of research data leads to lack of knowledge in practice*” (P111). These quotes underscore the need for a platform that not only collects data but also standardises it, ensures its quality, and provides a trustworthy mechanism for sharing it with the research community.

The survey confirmed a high level of awareness regarding the women's health gap. A majority (77% answered with a Likert score 4 and higher, $M = 3.99$, $SD = 0.92$) of respondents agreed with the statement: “Addressing sex- and gender-specific differences in health research will improve the quality of outcomes in my field.”

3.4 A Research-Ready Mcta Data Infrastructure

Based on the survey results, participants emphasised the importance of capturing a wide range of health data types – spanning core menstrual tracking, mental health, lifestyle, and psychosocial indicators. Ethical concerns such as privacy, user autonomy, and trust in data use ranked among the highest priorities, underscoring the need for infrastructures that support meaningful research while respecting individual privacy and preferences.

Table 3: Proposed Three-Tier Data Structure for Menstrual Research.

Layer	Description	Example Domains	Collection Method
Core	Universally relevant, low-burden data needed for most studies.	Menstrual cycle, bleeding, pain, mood and stress, sleep and activity, nutrition, reproductive symptoms, and socio-demographic	Self-report or passive sensing
Optional	Adds depth for specific research questions; medium burden.	Fertility and ovulation, cognition, substance use, endocrine metrics, and clinical history	Periodic self-report, user-activated modules with explicit consent
Sensitive	High-burden or privacy-critical data requiring explicit opt-in.	Medical diagnosis, gynaecological exams, hormonal tests, infertility, miscarriage, sexual preferences	Verified upload or clinical linkage, opt-in only, with layered consent

To address these needs, we propose a three-tiered data structure that balances research utility with participant burden and sensitivity (Table 3). This structure differentiates between core, optional, and sensitive data types based on their relevance and privacy implications.

Core data could be collected through routine cycle tracking and low-burden self-reports, while optional and sensitive data would be accessed via explicitly activated modules with layered consent. More broadly, the proposed data structure is platform-agnostic and could be implemented either within a newly developed research MCTA such as CyMe or through modular extensions of existing menstrual tracking applications that support interoperable data export or donation.

This modular model enables researchers to maintain high data quality standards while providing users with complete control over what is shared. A pseudonymous user is linked to a cycle, which contains both self-reported observations and passive measures. Each data type is tracked through a consent entity with a defined permission scope and timestamps.

Taken together, these findings provide a clear answer to RQ1: Researchers and healthcare professionals view a broad spectrum of data types – ranging from physiological to psychosocial – as essential for women’s health research. Collection preferences vary by domain, while ethical expectations consistently stress user autonomy and privacy-by-design.

4 DISCUSSION

Our findings highlight a strong need among researchers for high-quality, contextualised women’s health data. The prominence of psychosocial factors in the ratings signals a clear shift toward a holistic view of health – one that interprets biological data in relation to mental, social, and environmental influences. Researchers expressed strong interest in multi-domain data but emphasised the importance of ethical safeguards, particularly when working with sensitive data types. The relatively limited use of advanced analytic tools such as machine learning or time-series models (Symul et al., 2019), along with low adoption of interoperable standards like FHIR (Ryu et al., 2017), suggests a methodological gap that better infrastructure could help bridge.

These findings provide a direct answer to RQ2: researchers’ needs and ethical expectations can be addressed through a user-centred, privacy-preserving data architecture. The proposed three-tier model supports data collection at different levels of sensitivity and burden, aligning with users’ comfort while still meeting researchers’ analytical needs. Modular design combined with layered consent ensures that users retain complete control over their data while enabling the generation of high-quality, research-ready datasets.

While promising, this study has limitations. The expert sample was self-selecting and geographically narrow, with most respondents based in academia. Industry, policymaking, and user perspectives were underrepresented. Broader validation is needed. Future research should involve co-design workshops, expert interviews, real-world pilot testing of the data model, and continuous feedback loops to refine its usability and applicability.

5 CONCLUSION

This study provides empirical evidence to guide the development of a research-ready digital infrastructure for women’s health. By mapping researcher needs to a flexible, privacy-centric data model, we provide a blueprint for a research-ready MCTA that can address long-standing gaps in menstrual and reproductive health research. Our findings indicate that experts consider a broad range of biopsychosocial data essential for advancing the field and are highly motivated to utilize MCTA-derived datasets, provided they are collected ethically, transparently, and with user-controlled governance.

In line with the Scale-it-Up workshop's focus on advancing digital women's health, this work demonstrates how user-centred design, layered consent, and standardised data ontologies can transform current menstrual tracking tools into robust research infrastructures. By operationalising ethical, inclusive, and technically interoperable design principles, the proposed framework supports not only data quality and research utility but also the broader objective of scaling digital health innovation responsibly and equitably.

Next steps include finalising the data ontology and codebook for a research-ready MCTA, piloting an anonymised data-export feature, and expanding the data structure to encompass perimenopausal and post-reproductive health states. Ultimately, this study provides actionable guidance for developing digital systems that significantly advance women's health research at scale, aligning with global calls to close evidence gaps and promote more equitable, data-driven care.

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CONFLICT OF INTEREST

MN is affiliated with the Centre for Digital Health Interventions (CDHI), which oversees publicly and industry-funded projects. However, the present work was not externally funded, and no industry partners were involved in any aspect of the work.

REFERENCES

- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77-101. <https://doi.org/10.1191/1478088706qp0630a>
- Cunningham, A. C., Pal, L., Wickham, A. P., Prentice, C., Goddard, F. G., Klepchkova, A., & Zhaunova, L. (2024). Chronicling menstrual cycle patterns across the reproductive lifespan with real-world data. *Scientific Reports*, 14(1), 10172. <https://doi.org/10.1038/s41598-024-60373-3>
- Downing, A., & Perakslis, E. (2022). Health advertising on Facebook: Privacy and policy considerations. *Patterns*, 3(9), 100561. <https://doi.org/10.1016/j.patter.2022.100561>
- Earle, S., Marston, H. R., Hadley, R., & Banks, D. (2021). Use of menstruation and fertility app trackers: A scoping review of the evidence. *BMJ Sexual & Reproductive Health*, 47(2), 90-101. <https://doi.org/10.1136/bmjshr-2019-200488>
- Grando, A., Sottara, D., Singh, R., Murcko, A., Soni, H., Tang, T., & Whitfield, M. J. (2020). Pilot evaluation of sensitive data segmentation technology for privacy. *International Journal of Medical Informatics*, 138, 104121. <https://doi.org/10.1016/j.ijmedinf.2020.104121>
- Hohmann-Marriott, B. E., Williams, T., & Girling, J. E. (2023). The role of menstrual apps in healthcare: Provider and patient perspectives. *The New Zealand Medical Journal*, 136(1570), 42-53. <https://doi.org/10.26635/6965.5925>
- ICC – International Chamber of Commerce. (2025). *ICC/ESOMAR international code on market, opinion and social research and data analytics*. <https://iccwbo.org/news-publications/policies-reports/iccesomar-international-code-market-opinion-social-research-data-analytics/>
- Kelly, B. G., & Habib, M. (2023). Missed period? The significance of period-tracking applications in a post-Roe America. *Sexual and Reproductive Health Matters*, 31(4), 2238940. <https://doi.org/10.1080/26410397.2023.2238940>
- Morgan, H. (2016). 'Pushed' self-tracking using digital technologies for chronic health condition management: A critical interpretive synthesis. *Digital Health*, 2, 2055207616678498. <https://doi.org/10.1177/2055207616678498>
- National Academies of Sciences. (2024). *Overview of research gaps for selected conditions in women's health research at the National Institutes of Health: Proceedings of a workshop – in brief*. National Academies Press. <https://doi.org/10.17226/27932>
- Peters, S. A., & Woodward, M. (2023). A roadmap for sex- and gender-disaggregated health research. *BMC Medicine*, 21(1), 354. <https://doi.org/10.1186/s12916-023-03060-w>
- Petrušić, I., Ha, W. S., Labastida-Ramirez, A., Messina, R., Onan, D., Tana, C., & Wang, W. (2024). Influence of next-generation artificial intelligence on headache research, diagnosis and treatment: The junior editorial board members' vision – part 1. *The Journal of Headache and Pain*, 25(1), 151. <https://doi.org/10.1186/s10194-024-01847-7>
- Principe, M., Stebler, D., Sou, D., Kowatsch, T., & Nißen, M. (2024). CyMe [si:][mi:]: Personalized and seamless menstrual health tracking. In *Mensch und Computer 2024 – Workshopband* (pp. 10-18420). Gesellschaft für Informatik e.V. <https://doi.org/10.18420/muc2024-mci-demo-369>

Privacy International. (2025). *FLO: Research Findings. No Body’s Business but Mine: Vol 2*. <https://privacyinternational.org/sites/default/files/2025-05/period%20tracking%20with%20recs.pdf>

Public Health England. (2018). *Survey reveals women experience severe reproductive health issues*. <https://www.gov.uk/government/news/survey-reveals-women-experience-severe-reproductive-health-issues>

Ryu, B., Kim, N., Heo, E., Yoo, S., Lee, K., Hwang, H., & Jung, S. Y. (2017). Impact of an electronic health record-integrated personal health record on patient participation in health care: Development and randomized controlled trial of MyHealthKeeper. *Journal of Medical Internet Research*, 19(12), e401. <https://doi.org/10.2196/jmir.8867>

Schantz, J. S., Fernandez, C. S., & Jukic, A. M. Z. (2021). Menstrual cycle tracking applications and the potential for epidemiological research: A comprehensive review of the literature. *Current Epidemiology Reports*, 8(1), 9–19. <https://doi.org/10.1007/s40471-020-00260-3>

Smith, K. (2023, May 3). *Women’s health research lacks funding – these charts show how*. Nature. <https://www.nature.com/immersive/d41586-023-01475-2/index.html>

Sou, D., Stebler, D., Principe, M., Kowatsch, T., & Nißen, M. (2024). Please CyMe: Towards enhancing menstrual health awareness through customization and personalized visualization in a menstrual health app. In *Proceedings of Mensch und Computer 2024* (pp. 674–683). <https://doi.org/10.1145/3670653.3677475>

Symul, L., Wac, K., Hillard, P., & Salathé, M. (2019). Assessment of menstrual health status and evolution through mobile apps for fertility awareness. *NPJ Digital Medicine*, 2(1), 64. <https://doi.org/10.1038/s41746-019-0139-4>

The Lancet Regional Health – Americas. (2022). Menstrual health: A neglected public health problem. *The Lancet Regional Health – Americas*, 15, 100399. <https://doi.org/10.1016/j.lana.2022.100399>

U.K. Clinical Research Collaboration. (2025). *U.K. health research analysis 2014*. <https://www.ukcrc.org/wp-content/uploads/2015/08/UKCRCHealthResearchAnalysis2014-WEB.pdf>

World Economic Forum. (2024). *Women are second-class citizens when it comes to health: Closing the gap could be worth \$1 trillion*. <https://www.weforum.org/stories/2024/01/women-healthcare-gap/>

APPENDIX

Appendix A: Data Categories and Types

Table A4: Data Categories, Data Types and Explanations.

Data Category	Data Type	Explanation
Cycle and Fertility Tracking	Cycle Length Difference (CLD)	Variation in cycle length between months (e.g., > 9 days), a marker for irregularity
	Basal Body Temperature (BBT)	Temperature rise after ovulation – used in fertility awareness methods
	Cervical Mucus Quality	Texture/appearance changes with ovulation, self-observed indicator
	Menstrual Bleeding Pattern	Duration, intensity, spotting, irregularities
	Ovulation Day Detection	Based on LH tests, temperature, or app-based prediction
Reproductive Status and History	Reproductive stage and age at reproductive stage	e.g., premenopausal, perimenopausal, postpartum
	Hormonal contraception use	Influences cycle and symptom data
	Infertility history / IVF	Important for endotype or phenotype clustering, infertility diagnosis, and IVF treatment
	Lactation / breastfeeding	Affects hormone levels and ovulation
	Pregnancies	Gestational diabetes history, history of hypertensive disorders in pregnancy
	Pregnancy loss(es)	May require sensitive handling, often optional to report live births, still births, miscarriages
	Number of births	
Menarche age	The age at which a person experiences their first menstrual period	
	Sex-specific diagnoses	e.g., endometriosis, PCOS, PMDD, amenarroe, etc.

Table A4: Data Categories, Data Types and Explanations (cont.).

Data Category	Data Type	Explanation
Hormonal and Clinical Biomarkers	Estradiol	Key estrogen marker that peaks around ovulation; important for assessing cycle phase and fertility.
	Progesterone	A hormone that rises after ovulation; essential for luteal phase function and pregnancy maintenance.
	Anti-Müller-Hormon (AMH)	A marker of ovarian reserve; widely used in fertility research and PCOS diagnostics.
	CA-125	Protein biomarkers often elevated in endometriosis and certain gynecological conditions.
	Menstrual blood biomarkers	Emerging research area: menstrual blood contains proteins and molecules relevant to chronic conditions
	Luteinizing Hormone (LH) tests	Commonly measured in urine, surge indicates ovulation and is used in fertility tracking.
	Follicle-Stimulating Hormone (FSH)	Regulates follicle development, which is relevant to ovarian function, menopause staging, and fertility treatment.
	Testosterone	Androgen hormone imbalances can indicate PCOS or other endocrine disorders.
	Vaginal microbiome data	Analysis of bacterial composition linked to infections, fertility outcomes, and overall vaginal health.
	Thyroid hormones	Includes TSH, T3, and T4; thyroid function affects menstrual regularity, fertility, and pregnancy health.
Inflammatory markers	e.g., CRP, cytokines; elevated levels can indicate chronic inflammation relevant to gynecological conditions.	
Physical Symptoms	Cramps / pelvic pain	Common in menstruation or endometriosis
	Breast tenderness/swelling	Often occurs in the luteal phase.
	Headaches/migraines	Often linked to an estrogen drop before menstruation.
	Hot flashes/night sweats	Typical perimenopausal symptom
	Bowel changes	Diarrhea or constipation in cycle phases, often underreported
	Back pain	Frequently reported during menstruation or premenstrually.
	Bloating	Common peri-menstrual symptoms linked to hormonal shifts.
	Nausea/vomiting	May occur with severe cramps or hormonal fluctuations.
	Acne/skin changes	Often flare around ovulation or before menstruation.
	Joint/muscle pain	Can increase premenstrually or during menstruation.
Appetite changes/food cravings	Typical in the luteal phase; linked to hormonal changes.	
Sexual and Vaginal Health	Libido / sexual desire	Changes in sexual interest, often cyclical
	Vaginal dryness/lubrication	Reduced moisture, typical in perimenopause or the luteal phase
	Pain during intercourse (Dyspareunie)	Associated with endometriosis, dryness, or hormonal changes
	Vaginal pH	An indicator of estrogen status or infection risk, home test available
	Menstrual sex behavior	Whether and how sexual activity occurs during menstruation
Societal Factors	Stigma around menstruation/menopause	May limit honest reporting or willingness to participate.
	Cultural and gender norms	Expectations around femininity, sexuality, and motherhood influence health behaviors.
	Disclosure of sensitive experience	Topics like pregnancy loss, infertility, or sexual health can be challenging to report.
	Privacy and trust in data use	Concerns about data security and misuse shape participation.

Table A4: Data Categories, Data Types and Explanations (cont.).

Data Category	Data Type	Explanation
Stress and Recovery Physiology	Heart Rate Variability (HRV)	Varies across cycle phases, an indicator of stress or hormonal shifts
	Electrodermal Activity (EDA)	Measures skin conductance, stress response signal
	Calories burned at rest (BMR)	Marker for metabolic rate, used e.g., in postpartum depression prediction
	Physical activity level	Exercise data, activity intensity, contextual variable
	Perceived stress	Subjective rating or validated scale (e.g., PSS)
	Resting heart rate	The number of heartbeats per minute at rest; can fluctuate with cycle phase and stress.
	Respiratory rate	Number of breaths per minute at rest; may change with hormonal or stress-related factors.
Affective and Cognitive Symptoms	Mood variability	Mood swings, emotional sensitivity
	Irritability/withdrawal	Social withdrawal or increased sensitivity in premenstrual or menopausal phases
	Cognitive fog/fatigue	Reduced concentration, forgetfulness, tiredness
	Sleep disturbance	Trouble falling asleep, night wakings, non-restorative sleep
	Anxiety/worry	Heightened mental tension, often luteal or postpartum-related
	Depressive symptoms	Low mood, loss of interest or pleasure, fatigue, or negative thoughts that may vary across the menstrual cycle or life stages.

Appendix B: Top 10 Least Relevant and Burdensome Data Types

Table A5: Top 10 Least Relevant Data Types.

Data Category	Data Type	Mean	SD	N
Sexual and Vaginal Health	Sex behavior	2.36	1.08	81
Stress and Recovery Physiology	Calories burned at rest (BMR)	2.37	1.11	79
Stress and Recovery Physiology	Electrodermal Activity (EDA)	2.38	1.02	76
Cycle and Fertility Tracking	Cervical Mucus Quality	2.41	1.04	86
Reproductive Status and History	Menarche age	2.45	1.07	111
Sexual and Vaginal Health	Vaginal pH	2.49	1.17	82
Cycle and Fertility Tracking	Basal Body Temperature (BBT)	2.49	1.03	85
Hormonal/Clinical Biomarkers	Menstrual blood biomarkers	2.53	1.15	74
Sexual and Vaginal Health	Vaginal dryness/lubrication	2.53	1.23	81
Hormonal and Clinical Biomarkers	Anti-Müller-Hormon (AMH)	2.56	1.14	73

Table A6: Top 10 Least Burdensome Data Types.

Data Category	Data Type	Mean	SD	N
Physical Symptoms	Appetite changes/food cravings	1.96	1.07	89
Physical Symptoms	Acne/skin changes	1.99	1.05	91
Reproductive Status and History	Use of hormonal contraception	2.02	1.02	86
Cycle and Fertility Tracking	Cycle Start and End Date	2.02	1.05	84
Stress and Recovery Physiology	Resting heart rate	2.02	1.00	83
Reproductive Status and History	Number of births	2.06	0.97	89
Reproductive Status and History	Menarche age	2.06	0.93	80
Cycle and Fertility Tracking	Individual Cycle Length	2.07	1.01	85
Reproductive Status and History	Lactation/breastfeeding	2.07	1.00	82
Stress and Recovery Physiology	Respiratory rate	2.08	0.99	85