Family Context, Reproductive Experiences, and Digital Engagement in Relation to Women's Genetic Health Knowledge, Perceptions, and Communication

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Abstract

Genetic factors shape many women's health conditions across the life course, yet how women perceive genetic influences within family and digital contexts remains underexplored. We conducted a cross-sectional survey of 249 U.S. women examining associations among family structure, reproductive experiences, digital health engagement, and three perception outcomes: self-reported genetic knowledge, perceived importance of family health history, and perceived genetic impact. We found that larger family networks were associated with higher perceived importance of family history, while childbirth experience was associated with stronger perceived genetic impact. Digital engagement, particularly technology breadth and generative AI use, was consistently associated with higher perceived importance and impact. Age and family size were associated with distinct communication patterns across women's health topics. These findings highlight the role of digital engagement and life-course context in shaping genetic health salience, with implications for informatics tools supporting family-based risk communication.

Introduction

Genetic factors influence a wide range of health conditions, including many that affect women across the life course. Prior work has shown that genetics influences many women's health experiences, including age at menarche,[1] menopausal timing,[2] premenstrual and menstrual symptoms,[3,4] and risks for breast and other cancers.[5,6] Public health and genetics research further emphasizes that understanding family history and genetic risk is increasingly important for prevention and early detection of health conditions.[7,8,9] However, studies show that a great percentage of the population is unaware of this genetic influence, and thus may overlook opportunities to better manage their health .[10,11]

Beyond having similar health experiences, families often serve as a primary context in which women learn, interpret, and share health information.[12,13,14] Research on health communication in families shows that family members coordinate around health, caregiving, and everyday wellbeing through conversations, media, and technology.[15,16] These dynamics also appear in work on reproductive and women's health, such as menstrual and fertility tracking, pregnancy, and menopause.[17,18,19,20,21] In spite of this understanding of communication dynamics, we have insufficient understanding around how family structure, reproductive experience, and digital engagement are associated with women's perceptions of genetic health. These factors may influence people's ability to engage with their genetic health and technology's ability to support them in doing so.

To address this gap, we conducted a cross-sectional survey of 249 women in the United States. The survey collected information on participants' demographic characteristics, family structure, reproductive experiences, and engagement with digital health technologies, alongside measures of perceptions related to genetic health. We address the following research questions (RQs):

1. How are women's reproductive experiences and familial factors associated with their knowledge and perceptions of genetic health?
2. To what extent is health technology use associated with women's genetic health knowledge and perceptions?
3. How do life stage and family context relate to women's family communication topics and involved members around women's health experiences?

Understanding these relationships can inform the design of technologies that support the sharing of information around health experiences impacted by genetics across different family structures and life stages.

Methods

We conducted a cross-sectional online survey to examine associations between women's genetic health knowledge and perceptions, health technology use, and family communication behaviors regarding women's health experiences. In this section, we present our data collection, dependent and independent variables, and data analysis methods. *Survey Design and Data Collection.* We developed a structured survey with a set of close-ended questions following the

RQs. The survey included three sections: (1) background and perceptions of genetic influences on women's health, (2) learning and sharing practices regarding women's health topics within biological families, and (3) use of health technologies. To support participants in understanding the context of genetic influences in women's health, we referred to definitions of women's health[22] and genetic factors,[7] population-based and genetic testing studies when designing the survey items ,[1,23,2,24,6,5] and presented participants with specific examples and illustrations. At the beginning of the survey, we present a synthetic family tree [1] with annotated women's health conditions for members. We also provide explanations for genetic influence with linked references for each health topic [2]. The survey questions was iteratively refined through internal review and pilot testing to improve clarity and comprehension. We elaborate on question wording and choices in the variable sections.

The participants were recruited via Prolific [3] in 2025 using stratified sampling to approximate U.S. census age distribution of adult women.[25] Eligibility criteria included identifying as a woman and being aged 18 years or older, and currently living in the United States. The study was approved by the Institutional Review Board at University of California, Irvine. The survey is distributed online using QuestionPro [4], and participants provided informed consent prior to participation. A total of 256 participants completed the survey. After excluding incomplete responses and failed attention checks, the final analytic sample included 249 respondents.

Dependent Variables. Self-reported genetic health knowledge, perceived importance of family health history, and perceived genetic impact were defined as dependent variables for RQ1 and RQ2 (Table 1).[11,26] Each construct was measured using a single-item 5-point Likert question. We modeled these outcomes as ordered categorical variables to preserve their ordinal structure, where higher response values indicated greater perceived knowledge, importance, or impact.

Table 1: Dependent Variables for RQ1 and RQ2: Genetic Health Knowledge and Perceptions

Variable	Survey Question (Text)	Response Options
Genetic Health Knowledge	How much do you think you know about how genetics affect women's health?	5-point Likert scale (1–5) [5]
Perceived Importance of Family Health History	How important do you think it is to know about your family's health history, especially related to women's health issues?	5-point Likert scale (1–5) [6]
Perceived Genetic Impact	How much do you think genetics affects women's health conditions among all influencing factors?	5-point Likert scale (1–5) [7]

For RQ3, we conducted further analysis to examine the association between personal and familial factors (primarily age and family size) and family communication behavior about women's genetic health (Table 2). The variables included the topics being learned or shared and the family members learned or shared with. Each option in the multiple-item questions was analyzed as a binary variable. Additionally, we calculated the total number of topics learned or shared with family. Both the number of topics and the specific family members were used to assess the participants' communication breadth.

Independent Variables. Based on prior work, we considered demographic characteristics,[27] family context,[28,29] reproductive experiences,[30] and digital health technology engagement[31] as key predictors of genetic health perceptions and family health communication. Variables included in the final multivariable models were selected based on conceptual alignment with the research questions, and assessment of multicollinearity using variance inflation factors (VIF).

Demographics and Family Context. For demographic information, we considered age, race/ethnicity, education level, and household income. Age was grouped into 10-year intervals for interpretation of effect sizes. Race/ethnicity

[1] Similar to this example: Diagram showing three generation family tree.

[2] For example: Menstrual Patterns & Symptoms (If your grandmother, mother or sister experiences painful cramps or irregular periods, you might have a higher chance of experiencing them too.)

[3] https://www.prolific.com/

[4] https://www.questionpro.com/us/

[5] 1 = Not at all knowledgeable; 2 = Slightly knowledgeable; 3 = Moderately knowledgeable; 4 = Knowledgeable; 5 = Very knowledgeable

[6] 1 = Not at all important; 2 = Slightly important; 3 = Moderately important; 4 = Important; 5 = Very important.

[7] 1 = No impact; 2 = Slight impact; 3 = Moderate impact; 4 = High impact; 5 = A lot of impact

Table 2: Dependent variables for RQ3: Family communication behaviors around women's health

Variable	Survey Question (Text)	Response Options
Learned Topics	What aspects of your family's experiences related to women's health do you know about? (Select all that apply)	Menstrual Patterns & Symptoms; Pregnancy & Fertility Experiences; Menopause & Aging Changes; Women's Illness or Chronic Conditions; Body & Hormonal Changes Over Time; I have not shared my women's health experiences with my family; Other
People Learned From	Who did you learn about your family's women's health experiences from? (Select all that apply)	Mother; Father; Sister(s); Brother(s); Cousin(s); options including paternal/maternal grandparents and aunts/uncles; Grandparents' siblings; Parents' cousins; None; Other
Shared Topics	What aspects of you or your family's experiences related to women's health have you shared with your family? (Select all that apply)	Same as learned topics
People Shared With	Who have you shared your or your family's women's health experiences with? (Select all that apply)	Mother; Father; Siblings; Grandparents; Aunts/Uncles; Cousins; Children; Partner/spouse; Other (please specify): ________

was assessed using a multi-select item; categories were collapsed to ensure adequate cell sizes and model stability. Education level was treated as an ordered categorical variable. After initial examination, we excluded household income from the final regression model, since it had high collinearity with education and is not the focus of this study. Family context was primarily operationalized as the number of biological family members with whom respondents reported regular contact (Table 3) (family size). Because extreme response categories contained sparse observations, categories were collapsed for regression analyses. Given that family size reflects potential exposure to shared genetic information and intergenerational communication opportunities,[12] it was included as a structural predictor in models examining both perception outcomes and communication behaviors.

Table 3: Independent variables: Demographics and family context

Variable	Survey Question (Text)	Response Options
Age	What is your age in years?	Integer input
Race and Ethnicity	Which of the following best describes your racial or ethnic background? (Select all that apply)	6 options from "American Indian or Alaska Native" to "White"; Prefer not to answer; Other
Education Level	Highest education level completed	7 options from "No formal qualifications" to "Doctorate degree (PhD/other)"; Don't know / not applicable; Prefer not to answer
Household income	Household Income (USD)	13 options from "Less than $10000" to "More than $150000"; Prefer not to answer
Family Size	Approximately how many biological (genetic) family members are you regularly in contact with?	1-3; 4-6; 7-10; 11-20; 21-30; 31-40; 41-65; More than 65

Reproductive Experiences. Reproductive experiences were assessed through self-reported history of menstruation, childbirth, having a biological child who had begun menstruation, and menopause status (Table 4). These variables were included to capture life-course contexts in which genetic health considerations may become more salient. Binary indicators were constructed for childbirth history and having a menstruating child. Menstruation and menopause status were retained as categorical variables. Some of these variables were eventually excluded from final modeling, since all participants have menstruated, and menopause was collinear with child menstruation.

Digital Health Technology Engagement. Health technology use variables were derived from multi-select items assess-

Table 4: Independent variables: Reproductive experiences

Variable	Survey Question (Text)	Response Options
Menstruation	Have you ever menstruated?	Yes; No
Childbirth	Have you ever given birth?	Yes; No
Children Menstruation	Do you have a biological child who has started menstruation?	Yes; No
Menopause	Have you gone through menopause?	Yes; No; I am going through menopause

ing health information technology use and health management tool use[32,33] (Table 5). Prior research suggests that both exposure to specific digital tools and overall digital engagement may influence health knowledge and perceptions.[31] Therefore, we constructed (1) one binary variable for each technology use option and (2) a count variable representing technology breadth (number of technology categories selected) from the health information technology checklist for RQ2.

Table 5: Additional Independent variables for RQ2: Digital health technology engagement

Variable	Survey Question (Text)	Response Options
Health Information Technology Use	What types of technology do you use to find or learn about health information? (Select all that apply)	Search engines and health websites; Generative AI tools; Health apps; Social media or online communities; Communication with healthcare providers; I do not use technology for health information; Other
Health Management Tool Use	What technologies have you used for recording or managing your personal health information related to women's health? (Select all that apply)	Health apps; Wearables; Manual tracking; Medical records; I have not used any of the technologies above; Other

Data Analysis. All analyses were conducted using Python 3.10.13. Prior to statistical modeling, survey responses were cleaned and re-coded as needed, including collapsing sparse categorical levels and constructing derived variables. To examine factors associated with genetic health perceptions (RQ1), we conducted ordinal logistic regression, and estimated proportional-odds for each of the three outcomes: self-reported genetic health knowledge, perceived importance of family health history, and perceived genetic impact. These outcomes were modeled separately. Demographic characteristics, family size, and reproductive experience variables were included as predictors in base models. To assess whether digital engagement was associated with perceptions beyond these factors (RQ2), we extended the base models by adding digital health technology variables, including generative AI use and technology breadth. Nested models were estimated to examine incremental associations. Guided by studies informed by the Health Belief Model,[34,35] which suggests that knowledge may shape health perceptions, we estimated additional models for perceived importance and perceived genetic impact that adjusted for self-reported knowledge to assess whether associations with other predictors were independent of perceived knowledge. Statistical significance was evaluated at α= .05.

To examine associations between lifestage, family size, and family communication behaviors (RQ3), we conducted chi-square tests of independence for categorical checklist variables (topics and families learned or shared) and calculated effect sizes using Cramer's V. For analyses involving communication breadth (learning and sharing network size), Spearman rank correlations were estimated. Age was also categorized into 10-year groups, which reflect lifestage variation. For RQ3, p-values from Spearman correlations and chi-square tests were adjusted for false discovery rate using the Benjamini–Hochberg procedure.

Results

Descriptive Statistics. The final analytic sample included 249 participants. The mean age was 46.8 years (SD = 17.7; range: 18–83), with age groups distributed across the adult life course from age 18 to 84, approximating the distribution of adult women in the U.S. population.[25] Most participants identified as White (69.1%), followed by Black or African American (22.1%), with smaller proportions identifying as Asian (5.2%) or Hispanic/Latino (4.8%).

A majority reported having given birth (70.7%), and 61.0% held at least a bachelor's degree.
For the primary perception outcomes, self-reported perceived genetic health knowledge showed moderate levels overall, with most responses concentrated in the middle categories ("somewhat" and "moderately" knowledgeable). Perceived importance of family health history was high overall, with 61.4% selecting the highest category. Perceived genetic impact also showed strong endorsement, with 79.5% selecting "moderate impact" or "a lot of impact". Regarding digital engagement, 62.7% reported using health-related apps, and 31.7% reported using generative AI tools for health information.

RQ1: Family Size, Reproductive Experience, and Genetic Health Knowledge and Perceptions. We estimated separate proportional-odds ordinal logistic regression models for each of three outcomes: self-reported genetic health knowledge, perceived importance of knowing family health history, and perceived genetic impact on women's health (Table 6).

Table 6: RQ1 Base Model: Ordinal Logistic Regression for Genetic Health Knowledge and Perceptions

	Knowledge	**Importance**	**Impact**
Predictor	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age (per 10 years)	0.80** (0.69–0.93)	1.02 (0.87–1.20)	0.91 (0.78–1.07)
Education (ordered)	1.37 (0.86–2.16)	1.40 (0.85–2.31)	1.47 (0.91–2.37)
White (vs non-White)	0.90 (0.54–1.51)	0.96 (0.54–1.70)	0.70 (0.41–1.20)
Family size (per bin)	1.19 (0.98–1.44)	1.44*** (1.16–1.78)	1.09 (0.90–1.32)
Ever given birth (yes vs no)	1.26 (0.71–2.24)	1.52 (0.80–2.87)	2.36** (1.29–4.32)
Has menstruating child (yes vs no)	2.07* (1.15–3.71)	0.94 (0.49–1.83)	1.37 (0.75–2.51)
Notes: * $p < .05$, ** $p < .01$, *** $p < .001$. OR = odds ratio; CI = confidence interval.			

Demographic Factors. Among demographic variables, age was significantly associated with self-reported genetic health knowledge. For every 10-year increase in age, participants had 20% lower odds of reporting higher levels of perceived knowledge ($p < .01$). Age was not significantly associated with perceived importance of family health history or perceived genetic impact. Meanwhile, education level and race were not significantly associated with the three outcomes in adjusted models.
Family Context. Family size was positively associated with perceived importance of knowing family health history. Participants who reported contact with larger numbers of biological family members had 44% higher odds of rating family health history as important ($p < .001$). In contrast, family size was not significantly associated with self-reported knowledge or perceived genetic impact.
Reproductive Experiences. Reproductive experiences were differentially associated with perception outcomes. Having given birth was significantly associated with higher perceived genetic impact on women's health (OR = 2.36, $p < .01$), indicating that women with childbirth experience were more likely to endorse stronger genetic influence.
Overall, these results indicate that genetic health knowledge and perceptions are more significantly related to women's family and reproductive experiences, compared to general demographics.
We additionally estimated knowledge-adjusted models for perceived importance of family health history and perceived genetic impact on women's health. Specifically, self-reported genetic health knowledge was included as a covariate to assess whether previously observed associations were independent of perceived knowledge. After adjustment, the association between family size and perceived importance of family health history remained statistically significant (OR = 1.35, $p < .01$), suggesting that larger families were associated with greater perceived importance independent of knowledge. Similarly, childbirth history remained significantly associated with perceived genetic impact (OR = 2.31, $p < .01$). Self-reported genetic health knowledge was positively associated with both perceived importance (OR = 1.58, $p < .01$) and perceived genetic impact (OR = 1.74, $p < .001$), indicating that higher perceived knowledge corresponded to stronger endorsement of genetics in women's health.

RQ2: Health Technology Engagement and Genetic Health Perceptions. To examine the role of digital engagement, we estimated proportional-odds models including technology breadth (richness) and individual technology categories as predictors of self-reported genetic health knowledge, perceived importance of family health history, and perceived genetic impact on women's health (Table 7).

Table 7: RQ2 Technology Models: Associations with Self-Reported Genetic Health Knowledge, Perceived Importance of Family Health History, and Perceived Genetic Impact on Women's Health

	Knowledge	**Importance**	**Impact**
Predictor	OR (95% CI)	OR (95% CI)	OR (95% CI)
Technology Breadth	1.25* (1.02–1.52)	1.47*** (1.17–1.85)	1.27* (1.04–1.56)
Generative AI Use	1.62 (0.90–2.91)	2.45** (1.31–4.61)	1.92* (1.13–3.28)
Models adjusted for age, education, race, family size, and reproductive variables.			
* $p < .05$, ** $p < .01$, *** $p < .001$.			

Technology Breadth. Greater technology breadth was positively associated with all three perception outcomes in base models. One additional type of health-related technology used was associated with 25% higher odds of reporting greater genetic health knowledge, 47% higher perceived importance, and 27% higher perceived genetic impact.
Specific Technology Categories. Among individual technology categories, use of generative AI tools was significantly associated with stronger endorsement of both perceived importance of family health history (OR = 2.45, $p < .01$) and perceived genetic impact (OR = 1.92, $p < .05$). Other technology categories alone do to appear to have a significant association with the outcomes.

Table 8: Knowledge-Adjusted Models for Perceived Family Health History Importance and Perceived Genetic Impact

	Importance	**Impact**
Predictor	OR (95% CI)	OR (95% CI)
Technology Breadth	1.35* (1.04–1.75)	1.16 (0.91–1.48)
Generative AI Use	1.62 (0.78–3.35)	1.57 (0.84–2.93)
Genetic Health Knowledge	1.58** (1.20–2.08)	1.74*** (1.30–2.32)
All models adjusted for age, education, race, family size, and reproductive variables.		
* $p < .05$, ** $p < .01$, *** $p < .001$.		

We also additionally estimated knowledge-adjusted models for perceived importance of family health history and perceived genetic impact (Table 8). After including self-reported genetic health knowledge as a covariate, the association between technology breadth and perceived importance remained statistically significant (OR = 1.35, $p < .05$), whereas its association with perceived genetic impact and was no longer statistically significant. Self-reported knowledge was independently associated with both perceived importance (OR = 1.58, $p < .01$) and perceived genetic impact (OR = 1.74, $p < .001$). The variables remain VIF <2.

RQ3: Age, Family Structure, and Communication Patterns. To examine whether family communication topics varied by age and family structure, we conducted chi-square tests and Spearman correlation analyses for learned and shared topics and related family members (Table 1 and Table 3).
Age and Topic Engagement. Age was significantly associated with learning about pregnancy and fertility ($q < 0.1$, V=0.287), with younger participants more likely to report learning these topics. In contrast, engagement with menopause and aging increased with age, with significant associations observed for both learning ($q < .01$, V=0.312) and sharing ($q < .001$, V=0.396). Yet, age was not significantly associated with the total number of topics learned or shared. These indicate that women might tend to learn and share more about health topics related to their current or previous lifestage. For example, older women might learn and share more about menopause and aging compared to younger groups. Also, since the results for learned topics is accumulative, meaning that participants report on what they have ever learned, so older participants naturally learn about more topics, but the differences between learning and sharing shrink as the age group gets older.

Figure 1: Association Between Age (10-Year Groups) and Health Topics (χ^2 Tests)

Health Topic	χ^2	Cramér's V
Pregnancy and Fertility(Learned)	20.45*	0.287
Pregnancy and Fertility (Shared)	12.58†	0.225
Menopause and Aging (Learned)	24.29**	0.312
Menopause and Aging (Shared)	38.97***	0.396

Significance after FDR: * $q < .05$, ** $q < .01$, *** $q < .001$.
$\dagger q = 0.19$

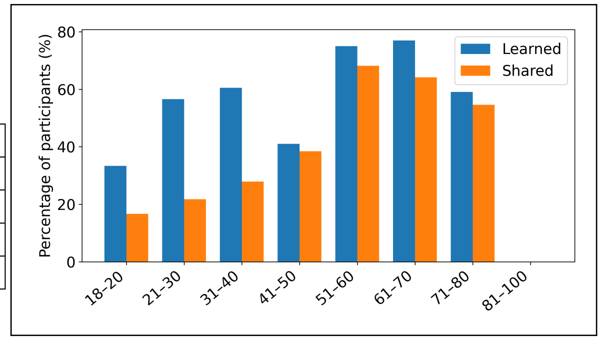

Figure 2: Age differences in learning and sharing about menopause and aging.

<u>Family Size and Communication Breadth.</u> For family communication breath, we examine both the number of topics communicated in the family, and family members communicated with. Family size was positively associated with the number of topics participants learned (Spearman's $\rho = .255$, $q < .001$) and shared ($\rho = .151$, $p < 0.05$), indicating broader topic exposure in larger families. At the relationship level, larger family size was significantly associated with learning from siblings ($p < .001$, V=0.345) and aunts/uncles ($q < 0.01$, V=0.284), as well as sharing with siblings ($p < .001$, V=0.320) and children ($p < 0.1$, V=0.251). No significant associations were observed for parents or grandparents. These results indicate that those who are in contact with larger families may have more information about their genetic health, both in terms of topic and from more relatives, especially extended families.

Figure 3: Association Between Family Size and Communication with Family Members (χ^2 Tests)

Relationship	χ^2	Cramér's V
Learning from Siblings	29.67***	0.345
Learning from Aunts/Uncles	20.02**	0.284
Sharing with Siblings	25.46***	0.320
Sharing with Children	15.74†	0.251

Significance after FDR: * $q < .05$, ** $q < .01$, *** $q < .001$.
$\dagger p < 0.05, q = 0.07$

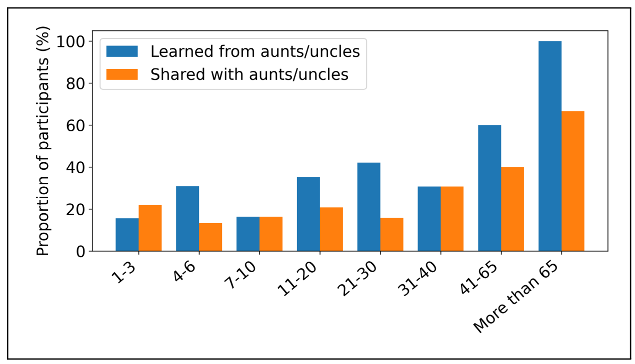

Figure 4: Proportions of participants reporting learning from and sharing with aunts/uncles across family sizes.

Discussion

This study examined how family structure, reproductive experiences, and digital technology use relate to women's perceptions of genetic health and their patterns of learning and sharing genetic health information. In this section, we summarize our findings and suggest future directions for technology and clinical informatics to promote women's health influenced by genetic factors. While prior work on genetic health communication has focused primarily on clinical contexts such as genetic counseling,[36,37] less is known about how everyday family and digital contexts shape lay perceptions of genetic health—a gap this study addresses.

Contextual Understanding of Genetic Impact. In RQ1 and RQ3, our findings suggest that knowledge and awareness of genetics' influence on health is significantly associated with life-course context. Participants with childbirth experience or menstruating daughters reported higher perceived genetic impact; women are also more likely to learn or share health topics closely related to their current stage. While existing clinical work often practice such as genetic counseling upon patients' immediate needs (such as at the point of diagnosis) ,[36,37] our finding suggests that technological opportunities to capture family history and hereditary risk information may be effective when aligned with life stages and embedded earlier on. This points to the value of supporting earlier and context-aware digital documentation of family history. Systems could enable family history collection and review to be embedded within visit types commonly associated with these life stages, such as prenatal care, gynecologic visits, or midlife health assessments. Capturing family history during these encounters may increase the completeness and relevance of recorded information, supporting more timely risk assessment and follow-up.

Prompting Genetic Health Knowledge and Awareness through Consumer Technology. Beyond clinical encounters, digital health tools for personal use, such as menstrual tracking tools,[38] AI chatbots,[39] or pregnancy health apps,[40] have been increasingly adopted by women who aim to track and manage their health experiences. In answering our RQ2, we also found that perceived genetic knowledge and use of digital technologies, particularly generative AI, were the strongest predictors of genetic health salience. Thus, future consumer health technologies could consider embedding information related to family health history genetic influence to promote users' learning and awarenss towards genetic health. Systems could support ongoing, lightweight reflection on family health experiences to help individuals organize informal knowledge before it enters clinical contexts, though longitudinal work is needed to confirm this direction.
Also, our findings surface that women in larger families may communicate more about their health impacted by genetic with relatives, and may also endorse the genetic impact more. Despite potential difficulties in engaging extended or remote family members in face-to-face conversations about their health experiences given timely, spatial or relational constraints,[41] research have proposed tools that support families' remote, asynchronous communication about daily health. Future systems could support documentation of family history while allowing space for sensemaking and interpretation around genetic impact, and thus filling in the gap between social communication and clinical usability.

Limitations This survey has several limitations. First, although stratified sampling was used to approximate U.S. age distribution, the sample does not equally present all racial and ethic groups. Participants who self-identify as Asian (5.2%) and Hispanic or Latino (4.8 %) are represented lower than their distribution in the general US population,[42] meaning that this study still may not represent experiences fully and may overlook disparities in health literacy and perceptions. The cross-sectional design also does not indicate causal inference; although digital engagement and perceived knowledge were associated with genetic health perceptions, the temporal direction of these relationships cannot be determined. Lastly, current standard measurements of perceived genetic health knowledge focus on understanding the details of genomics. This study, focusing on perceptions and familial factors, measures self-reported likert-scale items for our DVs; thus, the measurements may not serve as an standardized evaluation of participants' knowledge or awareness of genetic health, and are subject to reporting bias from single-item measures. Unmeasured confounders, such as health literacy, healthcare access, and prior clinical exposure to genetic risk information, may also account for part of the observed associations. Finally, no correction for multiple comparisons was applied to the regression models, and findings should be interpreted with appropriate caution.

Conclusion

Our study highlights the multifaceted factors shaping women's perceptions of genetic health and family-based communication patterns. We found that larger family networks were associated with broader learning and sharing behaviors. Meanwhile, perceived knowledge and digital technology engagement, particularly the use of genAI, were consistently associated with perceived genetic health knowledge and perceived importance and impact. Reproductive experiences further shaped perceived genetic impact, suggesting that life-course context influences how women interpret hereditary risk. These findings deepen our understanding of how structural, cognitive, and technological factors intersect in shaping genetic health awareness. Thus, we discuss design implications for health information systems that not only capture personal health information, but also support knowledge development and interpretation around genetic influence in context, bridging everyday digital engagement and clinically actionable genetic information.

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