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What are the perceptions, barriers and opportunities for spatial computing in health and self-care among UK adults? A cross-sectional online survey of the public and healthcare professionals

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ABSTRACT

Objectives To assess public and healthcare professional knowledge, attitudes, perceptions and behaviours regarding spatial computing technologies, virtual reality (fully immersive computer-generated environments), augmented reality (digital overlays on the physical world) and mixed reality (spatially anchored holograms) in healthcare, with a focus on perceived benefits for self-care and barriers to adoption in primary care and community settings.

Design Cross-sectional online survey.

Setting UK-wide, web-based survey conducted between January 2025 and August 2025.

Participants Community-dwelling adults aged ≥18 years residing in the UK, including healthcare professionals. A total of 405 respondents completed the survey; 41 were healthcare professionals.

Interventions No intervention was delivered. Participants completed a structured questionnaire assessing familiarity with spatial computing, perceived utility across self-care domains aligned to the Seven Pillars of Self-Care and perceived barriers to adoption.

Primary and secondary outcome measures Primary outcomes were self-reported familiarity with spatial computing technologies and perceived benefit across self-care domains. Secondary outcomes included perceived barriers to adoption and associations between demographic characteristics and familiarity. Analyses used descriptive statistics and exploratory inferential tests (χ^2, Fisher's exact, Friedman and Wilcoxon signed-rank tests with Bonferroni correction).

Results Most respondents (71.4%) reported familiarity with spatial computing technologies, although regular use was uncommon (4.7%). Oculus Quest (57.5%) and Apple Vision Pro (46.9%) were the most recognised platforms. Participants perceived strong potential for supporting health literacy, mental well-being and physical activity, particularly through guided mindfulness, avatar-led exercise and immersive patient education. Perceived benefit was lower for medication management and dietary guidance. Familiarity was statistically associated with gender ($p<0.001$), age ($p=0.002$) and ethnicity ($p=0.006$), with higher awareness among men, younger adults and some minority ethnic groups. The most frequently cited barriers to adoption were high cost (56.5% rating as critical), lack of training (67.4% rating 4–5) and data privacy concerns (63.5%).

Conclusions Spatial computing is viewed positively by the public and healthcare professionals as a tool to support self-care and aspects of healthcare delivery, particularly health literacy, mental well-being and physical activity. However, high cost, training gaps and privacy concerns remain substantial barriers. Targeted investment in evidence generation, workforce training and inclusive governance will be necessary to support equitable and responsible implementation.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ The survey instrument was grounded in an established public health framework (the Seven Pillars of Self-Care) and refined through pilot testing prior to launch.
⇒ Recruitment via Prolific Academic enabled rapid access to a demographically diverse adult sample across the UK within a structured, monitored online panel environment.
⇒ Convenience sampling via an online platform necessarily favours digitally literate participants, whereas groups most at risk of digital exclusion (older adults, those from lower socio-economic backgrounds) are likely under-represented.
⇒ The cross-sectional design and self-reported nature of responses preclude causal inference and may be subject to recall or social desirability bias.

BACKGROUND

Health systems face converging pressures of rising demand, workforce shortages and widening access gaps, trends that are particularly visible in UK primary care, where public dissatisfaction is closely tied to difficulties obtaining appointments and perceived staff shortfalls.[1] Against this backdrop, the

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strategic case for technologies that expand capacity, enhance patient engagement and enable prevention is compelling. Spatial computing is an umbrella term encompassing three related but technically distinct immersive modalities. Virtual reality (VR) immerses the user entirely within a computer-generated environment via a head-mounted display, fully occluding the physical world. Augmented reality (AR) overlays digital content onto the user's real-world environment, typically viewed through a smartphone, tablet screen or optical headset, without blocking the surrounding physical space. Mixed reality anchors holographic digital objects within the real environment in a spatially aware manner such that they appear to interact with physical surfaces and objects.[2–4] It allows digital content to be anchored in physical space, supporting embodied interactions that differ from conventional screen-based tools.

In the UK policy context, digital technologies are repeatedly highlighted as levers for service redesign and workforce enablement.[5] At the same time, the WHO situates self-care as a core pathway to universal health coverage, calling for evidence-based interventions that strengthen individuals' ability to promote health, prevent disease and manage illness.[6] Early applications of spatial computing in health are promising as randomised and controlled studies suggest that immersive VR can reduce acute and chronic pain in clinical settings, with growing methodological rigour and effect sizes that justify continued evaluation.[7–9] In neurorehabilitation, successive Cochrane-aligned syntheses report benefits of VR as an adjunct to conventional therapy after stroke, including upper-limb function gains.[10 11] In education and training, scoping and systematic reviews map expanding use across undergraduate and postgraduate curricula, with positive effects on skills acquisition and procedural rehearsal and mixed evidence on transfer to real-world performance.[12 13]

Conceptually, spatial computing has also been framed as a platform for next-generation, participatory 'metaverse' health experiences.[14] Yet translation beyond specialist contexts into primary care and community-based self-care remains limited. Real-world deployment hinges on integration with existing data infrastructure and workflows since most UK general practices use Egton Medical Information Systems (EMIS) or The Phoenic Partnership (TPP) SystmOne, which together cover more than 90% of English practices.[15] Current national programmes enabling patient access to general practitioner records through the National Health Service App illustrate the governance, interoperability and safety layers that any new modality must respect,[16 17] whereas parallel concerns focus on privacy, ethics and acceptability primarily because immersive systems capture high-granularity biometric, behavioural and spatial data (eg, eye-tracking, body motion), raising distinctive risks around inference, reidentification and exploitation.[18–20] Moreover, differential digital literacy persists across the population, with implications for equitable uptake of novel interfaces.[21]

In the UK, evidence and value expectations are increasingly codified since adoption decisions for digital health tools are guided by the National Institute for Health and Care Excellence Evidence Standards Framework, which specifies proportionate clinical- and economic-evidence requirements for deployment and scale-up.[22 23]

A further gap is conceptual. While 'digital health' is often discussed generically, spatial computing affords embodied, situated experiences that may differentially influence key behaviours underpinning self-care (eg, comprehension, motivation, adherence). The International Self-Care Foundation's Seven Pillars of self-care framework (knowledge and health literacy; mental well-being; physical activity; healthy eating; risk avoidance; good hygiene; and the rational use of products and services) offers a structured lens for anticipating where immersive modalities could add value.[24] Prior scholarship has proposed integrative frameworks for self-care and mapped measurement tools against these pillars, highlighting both the breadth of relevant behaviours and the scarcity of instruments that capture them comprehensively.[25 26]

This study addresses these evidence and implementation gaps by assessing the knowledge, attitudes, perceptions and behaviours of UK community-dwelling adults, including healthcare professionals (HCPs), toward spatial computing in health and self-care. We examine familiarity and perceived utility across self-care domains, explore barriers such as cost, training and privacy and test for demographic differences relevant to equity. By situating public and professional perspectives within UK primary-care realities and established evidence standards, the study aims to inform co-design priorities, evaluation strategies and governance approaches for the responsible introduction of spatial computing into routine care.

The primary aim of the Investigating the Use of Spatial Computing Technologies in Health & Care Settings (METACARE) study was to assess the knowledge, attitudes and practices of HCPs and the general public regarding the potential implementation of spatial computing technologies in healthcare, particularly in primary care and self-care settings. The study focused on measuring familiarity with consumer and professional spatial computing platforms, perceived utility across the seven pillars of self-care and attitudes toward their integration into existing models of care. Specifically, we sought to examine public awareness and prior use of spatial computing tools, to identify perceived benefits and challenges to adoption from both HCPs and community-dwelling adults and to explore how demographic characteristics such as age, gender and ethnicity shape familiarity and acceptance.

METHODS

Study design

This cross-sectional study aimed to explore the general knowledge, attitudes, perceptions and behaviours of a cross-section of UK adults, including health and care

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professionals, regarding the use of spatial computing technologies along with the sociodemographic factors which may affect them. The study employed a quantitative methodology using an electronic survey tool (eSurvey).

Survey instrument

A structured, self-administered electronic questionnaire was developed drawing on existing literature, expert input and public health frameworks on digital self-care. It included closed-ended items covering five domains: (1) familiarity and exposure to spatial computing devices (eg, Apple Vision Pro, Microsoft HoloLens, Oculus Quest)[27]; (2) perceived utility of spatial computing for health and well-being (5-point Likert scale); (3) perceived impact on self-care domains based on the Seven Pillars of Self-Care; (4) barriers and ethical concerns related to adoption in healthcare; and (5) sociodemographic characteristics. Familiarity was operationalised as a broad continuum, ranging from 'having heard of these devices but never used them' to 'using them regularly' and did not include validated items to distinguish surface-level brand awareness from functional understanding of the technology. Accordingly, familiarity as reported here should not be equated with technical competence, meaningful hands-on experience or informed evaluation of these devices. Prior to launch, the survey was piloted with 25 individuals, drawn from members of the research team, academic colleagues and a convenience sample not included in the main study (external pilot survey), to assess question clarity, logical flow and technical functionality on both desktop and mobile devices. Feedback from the pilot was used to refine question wording and adaptive logic before the survey was deployed in its final form. The questionnaire was developed de novo for this exploratory study and was not subjected to formal psychometric validation. No measures of internal consistency, test–retest reliability or structural validity were conducted, as the instrument was designed for descriptive and hypothesis-generating purposes rather than as a validated psychometric scale. The final version, hosted on Qualtrics, required approximately 10 min to complete.

Adaptive questioning was used so, for example, having experienced specific symptoms or having consulted one or more HCPs regarding these symptoms, led to the display of specific questions relating to these experiences. In its longest version, the survey was composed of 33 questions, including 9 for sociodemographic information such as age, gender and employment status. Other questions related to knowledge, attitudes and experiences. In its longest version, the survey was displayed over 13 pages, with a maximum of six questions per page. Respondents could not use a back button to revise their responses. The eSurvey was developed, revised and tested by the study team to ensure clarity, usability and technical functionality before dissemination. A copy of the full survey can be accessed in online supplemental file 1.

Data collection

This was an open eSurvey, accessible to anyone with the survey link. The voluntary survey required less than 10 min to complete, though the length may vary depending on the options selected. Accordingly, findings should be interpreted as descriptive and hypothesis-generating rather than estimates of population prevalence.

The link to the eSurvey was active on the Imperial College Qualtrics XLM platform between 17 January 2025 and 1 August 2025. The survey included a link to the participant information sheet, which informed potential respondents on the study's aims, the protection of participants' personal data, their right to withdraw from the study at any time, which data were stored, where and for how long, who the investigator was, the purpose of the study and survey length. Most participants were recruited via Prolific Academic's online panel,[28] which facilitates rapid access to demographically diverse adult samples but does not employ probability-based sampling. A formal participation rate cannot be calculated because recruitment included both the Prolific Academic panel and informal snowball dissemination through professional and personal networks, making it infeasible to determine the total number of individuals exposed to the survey link. Participants who did not complete all mandatory items were excluded automatically by the Qualtrics platform, and duplicate entries from the same IP address within a 24-hour window were identified and removed prior to analysis. A total of 405 fully completed responses were retained. The overall completion rate among those who initiated the survey (n=429) was approximately 94.4%. No cookies were used to track respondents between sessions. As Prolific panel participation requires internet access, digital literacy and prior engagement with online research, the resulting sample composition may not reflect the full spectrum of the UK population, particularly those with limited digital access. No incentives were offered for participation beyond standard panel reimbursement, where applicable. Personal and professional networks were mobilised to respond and further disseminate the eSurvey among potentially eligible participants.

Within the Prolific platform, the study was advertised to eligible registered users via a standardised study listing that included a brief description of the study's aims, estimated completion time (~10 min) and details of standard panel compensation. Eligible participants who viewed the listing and chose to participate were directed via a unique Prolific-generated URL to the Qualtrics-hosted survey. Outside of Prolific, the survey link was also disseminated on social media platforms (X, BlueSky and LinkedIn) and through the personal and professional networks of the research team, including academic colleagues, clinicians and institutional contacts. Recipients were encouraged to complete the survey themselves and to share the link with other potentially eligible individuals (ie, a snowball approach). No advertising or social media campaigns were deployed beyond these two channels.

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Informed consent was obtained from all participants at the beginning of the survey. They were informed that this was a voluntary survey. Data collected were stored on a secure database at Imperial College London and were only accessible to the research team. All responses were pseudoanonymised to ensure confidentiality.

Data analysis

Only questionnaires fully completed were included in the analysis. Duplicate entries from the same IP address within a 24-hour period were also eliminated before analysis. Descriptive statistics (frequencies and percentages) were used to summarise participant demographics and key response distributions. To assess relationships between demographic variables and familiarity with spatial computing, χ^2 tests of independence were conducted. Where expected cell counts were fewer than five, Fisher's exact test was used. Statistical significance was set at $p<0.05$.

All inferential analyses were exploratory and hypothesis-generating; no causal inference was intended. Perceptions of spatial computing across multiple self-care domains were compared using Friedman tests, which account for repeated measures on ordinal variables. Post hoc Wilcoxon signed-rank tests with Bonferroni correction were applied to identify specific differences between domain ratings. Similarly, comparisons of perceived adoption barriers were analysed using Friedman and Wilcoxon tests to identify statistically significant differences between ranked barrier severity scores. All analyses were performed using Stata V.18 (StataCorp LP, College Station, Texas, USA). The Checklist for Reporting Results of Internet ESurveys was used to guide reporting[29] (online supplemental file 2).

Patient and public involvement

Patients and members of the public were not involved in the design, conduct, reporting or dissemination plans of this research.

RESULTS

Demographic profile of respondents

A total of 405 community-dwelling adults participated in the METACARE study (tables 1 and 2), including 41 HCPs and 364 non-HCPs. Given the small size of the HCP subgroup, all findings about HCPs are reported descriptively only and should not be interpreted as representative of UK HCPs more broadly. The average time taken to complete the survey is, on average, 5 min 30 s. The full survey findings are illustrated in online supplemental table S1. Detailed item-level distributions are provided in online supplemental tables S2-S4.

After accounting for missing values, the largest proportion of respondents was aged 31–40 years (30.6%), followed by those aged 18–30 years (22.0%), 41–50 years (18.3%), 51–60 years (16.3%) and 61 years or older (12.8%). Gender distribution was relatively balanced, with 49.6% identifying as female, 50.1% as male and 0.2% as another gender identity. The sample was predominantly white (81.0%), with smaller proportions identifying as black/African/Caribbean British (6.2%), Asian/Asian British (5.9%), mixed/multiple ethnic groups (4.2%) and other ethnic backgrounds (2.7%). While minor levels of item non-response were observed across demographic variables, the sample reflected broad representation across age bands, gender identities and racial/ethnic groups, supporting meaningful analysis of public perspectives on spatial computing in health (table 1).

Table 1 Participants' demographics (N=405)

Variable	Frequency (percentage)		
	HCP (n=41)	Non-HCP (n=364)	Total
What is your age?			
18–30	11 (26.8%)	78 (21.4%)	89 (22.0%)
31–40	14 (34.1%)	110 (30.2%)	124 (30.6%)
41–50	4 (9.8%)	70 (19.2%)	74 (18.3%)
51–60	8 (19.5%)	58 (15.9%)	66 (16.3%)
61+	4 (9.8%)	48 (13.2%)	52 (12.8%)
What is your gender?			
Female	24 (58.5%)	177 (48.6%)	201 (49.6%)
Male	17 (41.5%)	186 (51.1%)	203 (50.1%)
Other	0 (0.0%)	1 (0.3%)	1 (0.2%)
What is your ethnicity?			
White	30 (73.2%)	298 (81.9%)	328 (81.0%)
Asian/Asian British	2 (4.9%)	22 (6.0%)	24 (5.9%)
Black/African/Caribbean British	6 (14.6%)	19 (5.2%)	25 (6.2%)
Mixed/multiple ethnic groups	1 (2.4%)	16 (4.4%)	17 (4.2%)
Other ethnic groups	2 (4.9%)	9 (2.5%)	11 (2.7%)

HCP, healthcare professional.

Familiarity with spatial computing technologies

Of the 405 survey participants, 71.4% reported being familiar with consumer-facing spatial computing or VR devices (ie, had used them briefly, regularly or at least heard of them but never used them). Only a small minority (4.7%) indicated they regularly used such technologies. Around one-third (33.3%) had used a spatial computing device briefly, while an equal proportion (33.3%) had heard of the technologies but never used them. Just over a quarter (28.6%) reported being not familiar at all. This distribution suggests that, while general awareness is relatively high, hands-on experience with spatial computing in everyday contexts remains limited (online supplemental table S1).

Exposure to spatial computing platforms

When asked about specific devices, the most widely recognised platforms were the Oculus Quest (57.5%) and Apple Vision Pro (46.9%). Fewer participants were

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Table 2 The association between demographics and familiarity with consumer-facing spatial computing or virtual reality devices

Variable	General level of familiarity with spatial computing technologies		P value
	Yes	No	
What is your age?			
18–30	70 (78.7%)	19 (21.4%)	0.002
31–40	91 (73.4%)	33 (26.6%)	
41–50	56 (75.7%)	18 (24.3%)	
51–60	47 (71.2%)	19 (28.8%)	
61+	25 (48.1%)	27 (51.9%)	
What is your gender?			
Female	127 (63.2%)	74 (36.8%)	<0.001
Male	162 (79.8%)	41 (20.2%)	
Other	0 (0.0%)	1 (100.0%)	
What is your ethnicity?			
Asian/Asian British	22 (91.7%)	2 (8.3%)	0.006
British Black/African/Caribbean	23 (92.0%)	2 (8.0%)	
Mixed/multiple ethnic groups	14 (82.4%)	3 (17.7%)	
Other ethnic groups	7 (63.6%)	4 (36.4%)	
White	223 (68.0%)	105 (32.0%)	

familiar with Google Cardboard (22.7%) or Microsoft HoloLens (11.6%). Notably, 22.5% of respondents indicated they had never heard of or used any spatial computing device. These findings illustrate a high level of public brand awareness for consumer VR products, particularly those marketed for entertainment, but lower visibility for enterprise-grade systems such as HoloLens, which are more relevant to professional healthcare settings (online supplemental table S1).

Perceived benefits for managing health and well-being

Participants showed strong optimism about spatial computing for health and well-being. The highest ratings were for avatar-guided physical activity (67.9% scoring 4–5), guided mindfulness (60.5%) and virtual support groups (56.6%), highlighting perceived value in mental health and peer support. Educational and behavioural applications were also endorsed, including VR simulations to understand health conditions (64.0%), interactive health education (57.5%), remote monitoring (53.6%) and customisable patient interfaces (52.6%). Overall, respondents viewed spatial computing as most valuable when it delivers immersive, visual and personalised interactions, particularly in mental health, exercise and health education (table 2).

Lower enthusiasm for medication and lifestyle management features

By contrast, participants were more cautious about spatial computing for structured health tasks. Fewer saw strong value in medication management (40.2%), visualising diet and nutrition (43.0%) or promoting adherence to lifestyle medicine (37.6%). This ambivalence may reflect limited exposure to such tools or doubts about their practicality in everyday health management (online supplemental table S1).

Barriers and concerns regarding adoption

Despite the generally positive outlook, respondents identified several obstacles that could slow the adoption of spatial computing in healthcare. High cost emerged as the most significant barrier, with over half of participants (56.5%) rating it as a major concern (5 out of 5). Other notable barriers included lack of training (67.4% rated four or 5), data privacy concerns (63.5%) and system complexity (63.0%). Participants also highlighted issues such as limited evidence of benefits, potential disruption to existing healthcare workflows and ethical considerations including patient consent, bias in algorithms and inequitable access. These findings highlight that while enthusiasm is high, successful integration will require addressing practical, technical and ethical challenges (online supplemental table S1).

Summary of trends

Overall, the results indicate that respondents perceived spatial computing to hold promise for self-care and health support, particularly in areas involving experiential learning, behaviour change and psychosocial engagement. Applications involving personalised health education, visualisation and remote interaction garnered the most enthusiastic support, while domains such as medication adherence and diet management were viewed more cautiously. The generally favourable response across a range of self-care domains highlights the emerging public readiness to engage with immersive technologies in health contexts, although with some reservations around specific functionalities. These perceptions will be critical in shaping future research, innovation priorities and implementation strategies for spatial computing in both clinical and community settings.

Demographics and familiarity with spatial computing technologies

To explore whether familiarity with consumer-facing spatial computing technologies varied by demographic characteristics, bivariate analyses were conducted using χ^2 and Fisher's exact tests where appropriate (table 2). For this analysis, 'familiarity' was defined as a self-reported 'yes' response to having knowledge of spatial computing or VR devices.

Gender was significantly associated with familiarity ($p<0.001$). A higher proportion of males (79.8%) reported familiarity compared with females (63.2%). Only one participant identified as 'Other' gender and reported no familiarity. This pattern suggests a notable gender disparity in exposure to or engagement with emerging immersive technologies, potentially reflecting broader gender gaps in digital confidence and technology use.

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Age group was also significantly associated with familiarity (p=0.002). Familiarity tended to be higher among younger participants: 78.7% of those aged 18–30 and 73.4% of those aged 31–40 reported familiarity, compared with 48.1% among those aged 61 years or older. The data indicate a clear downward trend in familiarity with increasing age.

Ethnicity was statistically associated with familiarity with spatial computing technologies (p=0.006). Higher reported familiarity was observed among participants identifying as British black/African/Caribbean and Asian/Asian British compared with white participants, while familiarity was lowest among those reporting other ethnic backgrounds. However, these subgroup estimates were based on small cell sizes and should be interpreted with caution. The survey did not capture socio-economic position, technology access pathways, occupational exposure or prior engagement with immersive technologies, all of which may confound observed associations. These patterns should not be interpreted as evidence of differential acceptability across ethnic groups, but rather as signals for further, adequately powered investigation.

Familiarity with spatial computing varied significantly by gender, age and ethnicity. Men and younger adults reported higher awareness, while familiarity was also notable among some minority groups. Older adults and women, who showed lower familiarity, may be more affected by barriers such as complexity, lack of training and privacy concerns. Conversely, groups with higher familiarity may be more willing to engage but remain constrained by systemic barriers such as cost (critical for 56.5% of respondents) and limited evidence of benefit. Tailored training, support and trust-building for less familiar groups, alongside wider efforts to address cost and infrastructure, will be key for equitable adoption.

Given the exploratory design and unequal subgroup sizes, these associations were not adjusted for multiple testing and should be interpreted as hypothesis-generating rather than confirmatory.

Perceived benefit of spatial computing

A Friedman test compared perceptions of spatial computing across seven self-care domains (health literacy, mental well-being, physical activity, healthy eating, risk avoidance, hygiene and rational use). Ratings on a 5-point Likert scale showed significant variation in perceived benefit ($Q(6)=275.86$, $p<0.001$), indicating differences in how participants valued spatial computing across domains (table 3).

Post hoc Wilcoxon tests (Bonferroni p<0.0024) showed that health literacy, mental well-being and physical activity were the highest-rated domains. Health literacy scored higher than healthy eating, hygiene, risk avoidance and rational use, but lower than physical activity and similar to mental well-being. Mental well-being and physical activity were both rated higher than all other domains. Healthy eating held an intermediate position, above risk avoidance and hygiene but below the top three. Risk avoidance ranked lowest, while hygiene and rational use clustered in the intermediate-low range with no significant difference between them.

The final ranking placed health literacy, mental well-being and physical activity as the highest perceived benefits, followed by healthy eating, then hygiene practices and rational use of products, with risk avoidance lowest. Participants therefore

Table 3 Pairwise Wilcoxon signed-rank test results comparing perceived benefit scores (1=not at all, 5=very much) of spatial computing across self-care pillars, with Bonferroni correction (significance threshold: p<0.0024)

Comparison		Z statistic	P value	Interpretation
Health literacy	Mental well-being	−2.177	0.0295	No significant difference than mental well-being
	Physical activity	−3.542	0.0004	Health literacy was rated significantly lower than physical activity
	Healthy eating	5.407	<0.0001	Health literacy was rated significantly higher than healthy eating
	Risk avoidance	10.180	<0.0001	Health literacy was rated significantly higher than risk avoidance
	Good hygiene practices	7.249	<0.0001	Health literacy was rated significantly higher than good hygiene practices
	Rational use of products	5.739	<0.0001	Health literacy was rated significantly higher than rational use of products
Mental well-being	Physical activity	−1.953	0.0508	No significant difference
	Healthy eating	6.478	<0.0001	Mental well-being was rated significantly higher than healthy eating
	Risk avoidance	10.447	<0.0001	Mental well-being was rated significantly higher than risk avoidance
	Good hygiene practices	7.798	<0.0001	Mental well-being was rated significantly higher than good hygiene practices
	Rational use of products	6.831	<0.0001	Mental well-being was rated significantly higher than rational use of products
Physical activity	Healthy eating	7.646	<0.0001	Physical activity was rated significantly higher than healthy eating
	Risk avoidance	10.813	<0.0001	Physical activity was rated significantly higher than risk avoidance
	Good hygiene practices	8.661	<0.0001	Physical activity was rated significantly higher than good hygiene practices
	Rational use of products	7.275	<0.0001	Physical activity was rated significantly higher than rational use of products
Healthy eating	Risk avoidance	5.605	<0.0001	Healthy eating was rated significantly higher than risk avoidance
	Good hygiene practices	3.104	0.0019	Healthy eating was rated significantly higher
	Rational use of products	0.373	0.7092	No significant difference
Risk avoidance	Good hygiene practices	−3.465	0.0005	Risk avoidance was rated significantly lower than good hygiene practices
	Rational use of products	−5.850	<0.0001	Risk avoidance was rated significantly lower than rational use of products
Good hygiene	Rational use of products	−2.330	0.0198	No significant difference

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viewed spatial computing as most valuable for improving literacy, well-being and physical activity (table 3 and figure 1).

Barriers to using spatial computing

The Friedman test showed significant variation in how barriers were ranked ($Q(9)=1000$, $p<0.0001$). High cost was consistently the top concern, rated significantly higher than all others. Lack of training and limited evidence formed the next tier, comparable to data privacy and complexity. Potential disruption clustered with these mid-level concerns. Lower-ranked barriers included lack of evidence, ethical issues, hygiene and other considerations, which were generally seen as less critical. The final hierarchy was: (1) high cost; (2) lack of training and limited evidence; (3) data privacy, complexity and disruption; (4) lack of evidence; (5) ethical concerns; and (6) hygiene and other. These findings highlight cost, training and evidence gaps as the most pressing challenges, with privacy and technical issues moderately important and ethical or hygiene concerns less influential (table 4 and figure 2).

DISCUSSION

Summary of principal findings

This study surveyed 405 UK-based community-dwelling adults, including a small subgroup of health and care professionals, to examine awareness, perceptions and perceived risks and benefits of spatial computing technologies in healthcare. Most participants reported general familiarity with VR or AR devices, though only a small minority reported regular use. Among those familiar, the most recognised platforms were Oculus Quest and Apple Vision Pro-consumer-facing devices primarily marketed for entertainment, while familiarity with enterprise-focused devices such as Microsoft HoloLens was limited.

Despite modest hands-on exposure, participants expressed strong optimism about the potential of spatial computing to support health and well-being, particularly through applications like guided mindfulness, avatar-led fitness demonstrations, immersive patient education and virtual peer support. Health literacy emerged as the most strongly endorsed self-care domain, followed by physical activity and mental well-being. However, enthusiasm waned when participants considered spatial computing for medication management or dietary guidance, suggesting variable acceptability across use cases.

Inferential findings, which should be interpreted as exploratory signals rather than confirmatory evidence, highlighted a significant gender-based disparity with men being markedly more likely than women to report familiarity with spatial computing technologies. Statistically significant associations were also observed between familiarity with spatial computing and certain sociodemographic characteristics, including age and ethnicity. However, observed differences by ethnicity should be interpreted cautiously, as subgroup sizes were small and the survey did not collect data on socio-economic

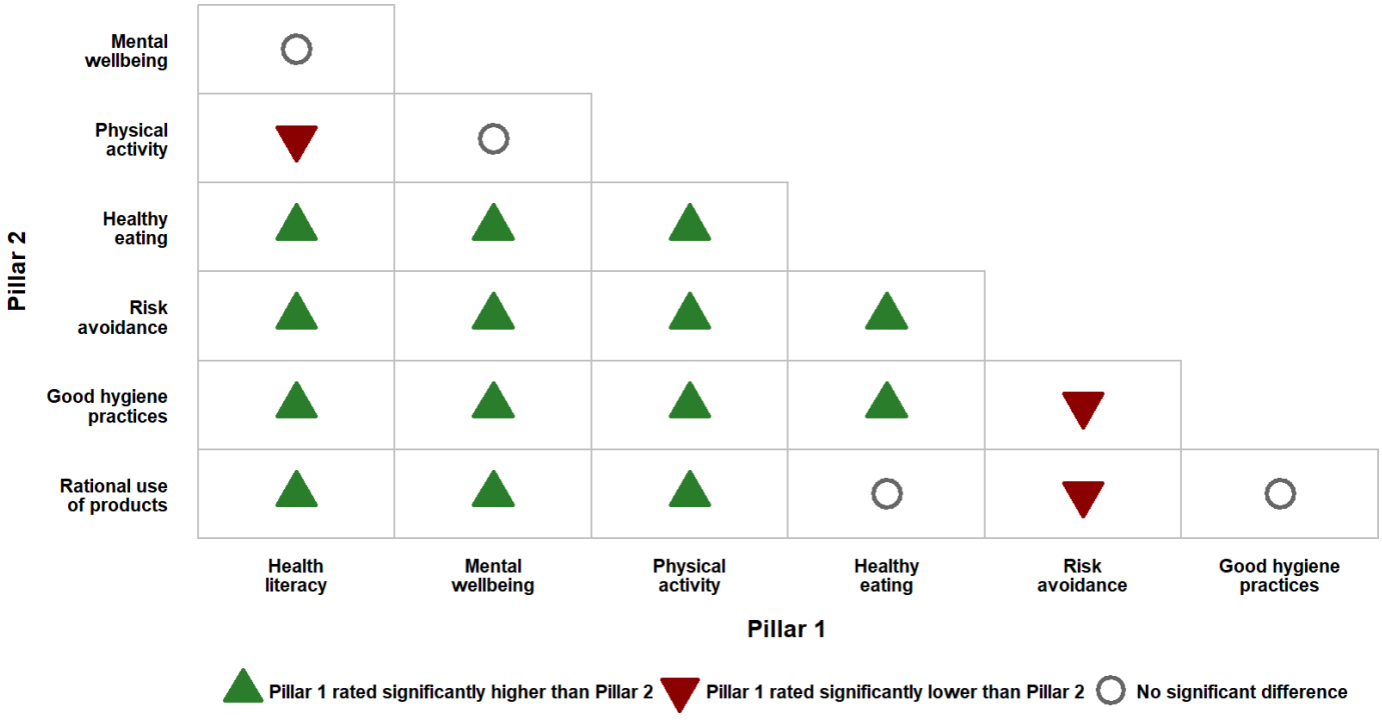


Figure 1 Pairwise comparison of perceived benefits of spatial computing across self-care domains based on Wilcoxon signed-rank tests with Bonferroni correction for multiple comparisons. The matrix displays upper-triangle comparisons only. Green upward triangles (▲) indicate that the self-care domain on the x-axis (Pillar 1) was rated significantly higher than the domain on the y-axis (Pillar 2); red downward triangles (▼) indicate the opposite. Grey open circles (○) denote no statistically significant difference. Domains are ordered consistently across axes to facilitate interpretation. Adjusted significance threshold derived using Bonferroni correction across all pairwise comparisons.

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Table 4 Pairwise Wilcoxon signed-rank test results comparing perceived barrier severity (1=not at all, 5=very much) to spatial computing adoption, with Bonferroni correction (significance threshold: p<0.0011)

Comparison		Z statistic	P value	Interpretation
High cost	Lack of training	9.398	0.0001	High cost rated significantly higher than lack of training
	Limited evidence of benefits	11.633	0.0001	High cost rated significantly higher than limited evidence
	Potential disruption	13.220	0.0001	High cost rated significantly higher than potential disruption
	Data privacy concerns	7.376	0.0001	High cost rated significantly higher than data privacy
	Complexity	10.314	0.0001	High cost rated significantly higher than complexity
	Lack of evidence	12.688	0.0001	High cost rated significantly higher than lack of evidence
	Ethical concerns	13.020	0.0001	High cost rated significantly higher than ethical concerns
	Hygiene considerations	15.689	0.0001	High cost rated significantly higher than hygiene considerations
	Other	16.224	0.0001	High cost rated significantly higher than other
Lack of training	Limited evidence of benefits	4.472	0.0001	Lack of training rated significantly higher than limited evidence
	Potential disruption	8.300	0.0001	Lack of training rated significantly higher than potential disruption
	Data privacy concerns	−0.607	0.5441	No significant difference
	Complexity	0.537	0.5912	No significant difference
	Lack of evidence	6.218	0.0001	Lack of training rated significantly higher than lack of evidence
	Ethical concerns	8.164	0.0001	Lack of training rated significantly higher than ethical concerns
	Hygiene considerations	14.441	0.0001	Lack of training rated significantly higher than hygiene considerations
	Other	14.242	0.0001	Lack of training rated significantly higher than other
Limited evidence of benefits	Potential disruption	3.937	0.0001	Limited evidence rated significantly higher than potential disruption
	Data privacy concerns	−4.524	0.0001	Limited evidence rated significantly lower than data privacy concerns
	Complexity	−3.876	0.0001	Limited evidence rated significantly lower than complexity
	Lack of evidence	2.838	0.0045	No significant difference
	Ethical concerns	4.578	0.0001	Limited evidence rated significantly higher than ethical concerns
	Hygiene considerations	12.025	0.0001	Limited evidence rated significantly higher than hygiene considerations
	Other	12.836	0.0001	Limited evidence rated significantly higher than other
Potential disruption	Data privacy concerns	−7.916	0.0001	Data privacy concerns rated significantly higher than potential disruption
	Complexity	−7.659	0.0001	Complexity rated significantly higher than potential disruption
	Lack of evidence	−1.894	0.0583	No significant difference
	Ethical concerns	1.688	0.0915	No significant difference
	Hygiene considerations	10.642	0.0001	Potential disruption rated significantly higher than hygiene considerations
	Other	11.690	0.0001	Potential disruption rated significantly higher than other
Data privacy concerns	Complexity	1.048	0.2948	No significant difference
	Lack of evidence	6.284	0.0001	Data privacy concerns were rated significantly higher than the lack of evidence
	Ethical concerns	9.070	0.0001	Data privacy concerns rated significantly higher than ethical concerns
	Hygiene considerations	14.324	0.0001	Data privacy concerns rated significantly higher than hygiene considerations
	Other	14.078	0.0001	Data privacy concerns rated significantly higher than other
Complexity	Lack of evidence	5.910	0.0001	Complexity rated significantly higher than lack of evidence
	Ethical concerns	8.344	0.0001	Complexity rated significantly higher than ethical concerns
	Hygiene considerations	14.176	0.0001	Complexity rated significantly higher than hygiene considerations
	Other	14.057	0.0001	Complexity rated significantly higher than other
Lack of evidence	Ethical concerns	3.414	0.0006	Lack of evidence rated significantly higher than ethical concerns
	Hygiene considerations	11.657	0.0001	Lack of evidence rated significantly higher than hygiene considerations
	Other	12.435	0.0001	Lack of evidence rated significantly higher than other
Ethical concerns	Hygiene considerations	8.965	0.0001	Ethical concerns rated significantly higher than hygiene considerations
	Other	9.974	0.0001	Ethical concerns rated significantly higher than other
Hygiene considerations	Other	5.034	0.0001	Hygiene considerations rated significantly higher than other

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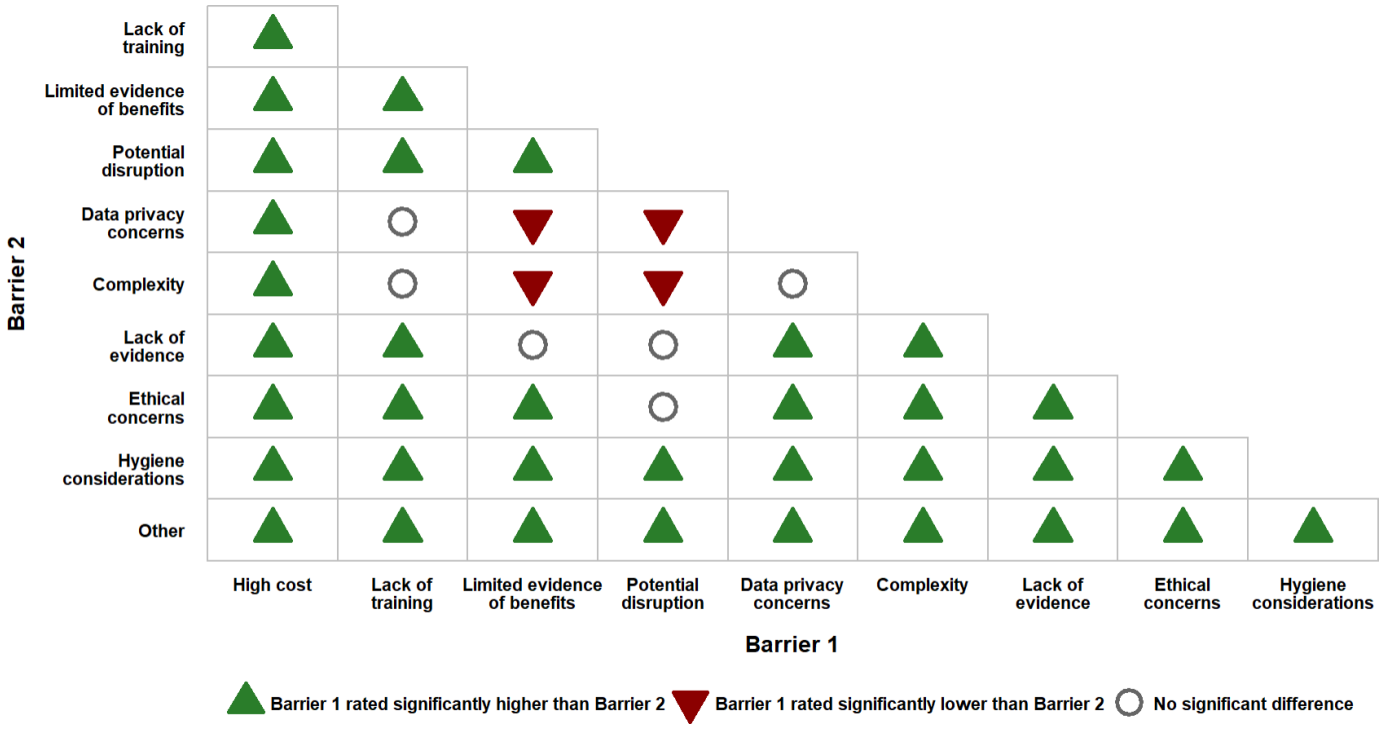


Figure 2 Pairwise comparison of perceived barriers to adoption of spatial computing based on Wilcoxon signed-rank tests with Bonferroni correction for multiple comparisons. The matrix displays upper-triangle comparisons only. Green upward triangles (▲) indicate that the barrier listed along the top axis (Barrier 1) was rated as significantly more important than the barrier listed along the side axis (Barrier 2). Red downward triangles (▼) indicate the reverse, that Barrier 2 was rated as significantly more important than Barrier 1. Grey open circles (○) indicate no statistically significant difference between the paired barriers after Bonferroni correction (adjusted significance threshold: p<0.0011). Barriers are ordered by overall perceived importance from left to right and top to bottom.

status, technology access pathways or prior occupational exposure, which may confound apparent associations. Perceived barriers to adoption were also stratified. In particular, while higher familiarity was observed in some minority ethnic categories, these groups comprised relatively small numbers of participants, limiting the precision and generalisability of these estimates. High cost was consistently ranked as the top obstacle, followed by lack of training, limited evidence of benefits and concerns around data privacy and system complexity.

Interpretation in the context of existing literature

The findings of the METACARE study align with emerging literature that suggests spatial computing holds promise as an enabler of digital self-care, patient education and health engagement (applications such as VR therapy, AR-assisted rehabilitation and immersive education have shown efficacy in clinical trials and pilot studies, particularly for chronic pain, phobias, poststroke rehabilitation and mental health support). However, much of this literature is hospital-based or specialist-led. METACARE expands this evidence base by gauging public sentiment on the broader use of these tools in everyday, community-based self-care.

Our findings corroborate the results of other studies,[30–33] confirming that VR interventions in healthcare are generally well-received by users when aligned with behavioural and psychosocial goals. In the present study, support was strongest for uses that offer visualisation, simulation and interactive feedback, mechanisms that may promote cognitive engagement and enhance health literacy. The high ratings for avatar-led exercise and guided mindfulness reinforce the potential for immersive tools to facilitate adherence to health-promoting routines, especially when aligned with personalised or gamified models of care.

However, scepticism around applications like medication adherence, diet tracking or procedural support may reflect current limitations in usability and real-world integration. These more structured health behaviours require precision, continuity and seamless electronic health record integration features not yet widely demonstrated by existing consumer-grade platforms. The relatively lower ratings for these domains may also reflect broader digital hesitancy or concern about over-reliance on immersive technologies in clinical care.

The strong perception of spatial computing's potential to improve health literacy is particularly outstanding. As self-care continues to be prioritised globally, tools that can enhance individuals' ability to access, comprehend and act on health information are invaluable.[26] Spatial computing can visualise anatomy, simulate disease progression or demonstrate therapeutic actions offering

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more accessible ways of communicating complex health information, particularly for people with lower baseline literacy or linguistic barriers.[34]

Regarding barriers, the predominance of cost concerns echoes similar findings from studies on digital health tool adoption.[35 36] Spatial computing hardware remains expensive and unless scaled through national programmes or insurance models, may deepen inequities. Similarly, the perceived lack of training and evidence highlights the importance of parallel investments in workforce development and robust clinical trials to validate new applications.

The gender gap in familiarity, where men were significantly more likely to report prior knowledge or use of spatial computing, echoes wider digital confidence disparities.[21] Addressing this imbalance may require more inclusive design, gender-sensitive training resources and targeted community engagement. Familiarity declined significantly with increasing age, with those aged 61 years or older showing the lowest rates of familiarity, compared with those aged 18–30 years. This age-related gradient warrants particular attention in the context of equitable adoption especially since older adults, who often stand to benefit most from digital tools supporting independent living and chronic disease management, appear least prepared to engage with these technologies.

Strengths and limitations of this study

To our knowledge, our study is among the first UK-based investigations to systematically examine public and HCP perceptions of spatial computing, specifically in relation to self-care and primary care contexts. The survey instrument was theoretically grounded, drawing on established public health and self-care frameworks, including the Seven Pillars of Self-Care, and was refined through pilot testing to ensure clarity and usability. The inclusion of both community-dwelling adults and HCPs, alongside detailed demographic data, enabled exploration of equity-relevant differences in familiarity and perceived utility. Analytically, the use of non-parametric, rank-based methods allowed appropriate comparison of perceived benefits and barriers across multiple self-care domains while respecting the ordinal nature of Likert-scale data.

The principal limitation of this study was that it employed convenience sampling via an online survey platform, which necessarily favours individuals with internet access, higher digital literacy and greater engagement with emerging technologies. As such, the sample cannot be considered representative of the UK population, and groups most at risk of digital exclusion, including some older adults, individuals from socioeconomically deprived backgrounds and those with disabilities, are likely underrepresented. Findings should therefore be interpreted as reflecting the views of a digitally engaged segment of the public rather than population-level attitudes. Critically, the high familiarity rate reported in this study should not be interpreted as a population-level prevalence estimate. Prolific Academic panellists, by definition, have internet access, active digital accounts and prior experience with online research participation, characteristics that are strongly correlated with awareness of emerging technologies. The true rate of familiarity with spatial computing among the broader UK adult population is likely considerably lower, particularly among older adults, individuals with lower formal education and those in areas with poor digital infrastructure. Moreover, the HCP subgroup was small, limiting the study's ability to draw meaningful conclusions about HCP perceptions as a distinct analytical stratum. As no adequately powered subgroup comparisons between HCPs and non-HCPs were performed, any apparent differences in this sample should be treated as hypothesis-generating.

Second, familiarity, attitudes and perceived benefits were self-reported and may be subject to recall bias or social desirability bias. Reported familiarity does not necessarily equate to sustained or competent use, particularly given that regular use of spatial computing devices was uncommon in this sample. Third, although statistically significant associations were observed between familiarity and demographic variables such as gender, age and ethnicity, some subgroup sizes, particularly within ethnic minority categories and among HCPs, were small. These analyses were exploratory and unadjusted for multiple testing; accordingly, observed associations should be treated as hypothesis-generating rather than confirmatory.

The third main limitation is the absence of validated measures of digital literacy and socio-economic status. Since both are strongly implicated in technology access and adoption behaviour, their absence means that observed associations, particularly those involving ethnicity and age, may partly reflect underlying socioeconomic and digital access disparities rather than attitudinal differences.

Fourth, all inferential analyses were limited to unadjusted bivariate tests. The absence of multivariable modelling adjusting simultaneously for age, gender, ethnicity and digital literacy means that apparent demographic associations may partly reflect confounding. Readers should exercise caution in attributing observed differences in familiarity to any single variable in isolation.

Finally, the cross-sectional design precludes any inference about causality or temporal change. Perceptions captured at a single time point may evolve rapidly as spatial computing technologies mature, costs change and evidence accumulates. Longitudinal and mixed-methods studies, as well as purposefully stratified samples, will be essential to assess how familiarity, acceptability and equity implications develop over time and in real-world implementation settings.

Implications for practice, policy and research

The findings of this study have several important implications. First, they highlight the growing public receptivity to immersive technologies in healthcare, particularly in domains such as mental well-being, physical activity and health education. Policymakers and digital health

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developers should capitalise on this receptivity by prioritising co-designed applications that reflect user preferences and address their concerns, especially regarding privacy, usability and equity.

Second, integration into self-care and primary care pathways will require technical innovation coupled with robust evidence of impact. Trials evaluating cost-effectiveness, clinical outcomes and behavioural changes resulting from spatial computing interventions are urgently needed. Future studies should also explore long-term engagement and potential harms, including over-reliance, cybersickness or exacerbation of digital exclusion.

Third, our data highlight the need for targeted digital literacy initiatives, particularly for women and older adults who appear less familiar with these technologies. Community-based workshops, primary care integration pilots and educational campaigns could help narrow this gap and promote equitable uptake.

Finally, the ethical and regulatory context must evolve in tandem. Concerns around data privacy, algorithmic bias, consent and equitable access remain salient. As spatial computing platforms become increasingly intertwined with artificial intelligence decision-support systems, safeguards must be established to ensure transparency, accountability and trustworthiness. National frameworks for immersive health technologies, analogous to those developed for telehealth and mobile apps, will be essential to guide ethical deployment.

By providing the first UK-wide snapshot of public and professional perceptions of spatial computing framed explicitly through a self-care lens, this study establishes a baseline against which future implementation trials, policy evaluations and equity-focused deployment strategies can be assessed.

CONCLUSION

Spatial computing represents a promising frontier in the evolution of digital health, with strong perceived value for self-care, patient education and public health engagement. This study offers timely and actionable insights into how the UK public perceives these tools, highlighting optimism for immersive applications that support mental health, health literacy and behavioural change. At the same time, it highlights important barriers, including cost, training gaps and digital confidence disparities, that must be addressed to ensure equitable adoption. As spatial computing matures, its integration into mainstream healthcare must be guided by inclusive design, rigorous evaluation and robust governance.

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Contributors AE-O conceived the study, led the study design, oversaw data collection, conducted the analysis and drafted the manuscript. CSQ, AA, MA and SA contributed to survey development, interpretation of findings and critical revision of the manuscript. All authors reviewed and approved the final manuscript and agree to be accountable for all aspects of the work. AE-O is the guarantor.

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Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Ethics approval This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Imperial College London Research Ethics Committee (reference number: 21IC7375). All participants were provided with a participant information sheet and gave informed consent electronically before taking part in the survey.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon reasonable request. De-identified data supporting the findings of this study are available from the corresponding author on reasonable request. The data are not publicly available due to ethical restrictions related to participant confidentiality and consent.

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