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What are the valued attributes and perceived risks of harm in digital technologies and AI-enabled digital coaches among youth living with chronic musculoskeletal pain? An exploratory, mixed-methods study

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ABSTRACT

Youth (16–24 years) experiencing chronic musculoskeletal pain (CMP) value access to digitally-supportive care. Adopting a three-phase design, we aimed to identify and validate youth's preferences for digital health solutions (DHSs) to support their CMP self-care and measure their preferences for artificial intelligence (AI)-enabled digital coaches and perceived risks of harm. Phase 1 involved focus groups with 20 youth experiencing CMP, applying content analysis to explore the attributes they consider when choosing digitally-supportive care. Phase 2 involved a two-round eDelphi (n=20 youth) to validate attributes identified in Phase 1, rank the importance of digital coach-related attributes, and identify risks of harm with digitally-supportive CMP care. Phase 3 involved two discrete choice experiments (n=41 youth) to measure preferences for digital coach-related attributes and risks of harm. Phase 1 produced 31 discrete attributes of DHSs (11 digital coach-related). Phase 2 validated 31 attributes and identified six risks of harm. Phase 3 identified three most preferred digital coach-related attributes (sample mean[SD] weights representing relative importance): 'Generates a pain self-care plan' (19.6[14.5]%), 'Learns my preferences for my pain self-care' (15.9[12.9]%), and 'Supports my healthcare visits' (11.1[12.4]%). The three most concerning risks of harm were: 'Quality of pain care advice and guidance' (31.8[17.3]%), 'Information being consistent with advice from my healthcare team' (25.8[17.5]%), and 'Data security protections' (14.8[17.6]%). Youth consider a range of attributes and potential harms of DHSs to support their CMP care; a subset appears to be most important. These attributes and risks of harm should be considered in co-design of digitally-supportive CMP care for youth.

Perspective: The results identify that a subset of digital coach-related attributes and risks of harm dominate youth's preferences for digitally-supportive chronic musculoskeletal pain care. These attributes and risks of harm should be considered in co-design of digital health solutions, and in positioning a solution within a clinical care ecosystem.

Introduction

Chronic musculoskeletal pain (CMP) imposes a substantial burden

among affected youth aged 16–24 years ('youth'). Systematic review-level evidence suggests that approximately 1 in 5 youth experience CMP,^{1,2} which commonly impacts their physical, emotional and social

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wellbeing.³⁻⁷ These impacts occur at a developmentally vulnerable time in their life, as they move from adolescence to adulthood and navigate complex biological, emotional and social changes while forging a sense of self and identity. These challenges are further compounded when CMP co-exists with mental health condition(s),^{8,9} manifesting as a bi-directional load.^{3,4} At the same time, this age range represents a critical period in which youth transition from paediatric to adult health services. The impact of CMP on youth also has socioeconomic implications. For example, total productivity losses in Australia are estimated between \$AUD 15–27 billion or more annually, with direct costs among 16–24 year olds contributing up to \$AUD 4 billion.¹⁰ In this context, health services that are responsive to youth’s needs and that mitigate care inequities are needed.¹¹⁻¹⁴

Youth living with CMP desire independence and to be supported in their care as they transition into adulthood, including by digital health solutions (DHSs),¹⁵ and related health services.¹⁶ Recent technological advances harnessing artificial intelligence (AI) have potential to support youth’s self-care and healthcare needs, including clinical encounters, care coordination, and navigation.^{11,17} Youth with chronic conditions value attributes of DHSs that include design and functionality, privacy and sharing, personalisation, and interactivity.¹⁸ However, for youth living with CMP, the relevance of these previously identified attributes of DHSs is unknown.

Digital coaching, as a specific function of DHSs, shows promise for supporting self-care, for example, in people living with type 2 diabetes or mental health conditions.^{19,20} Specific attributes such as timing of messages, content of behavioural cues, and trust, influence users’ experiences of, and preferences for, digital coaching.²¹ Although DHS co-design is a globally-recommended best-practice,²² there is no evidence about the attributes of digital coaches specific to CMP care that youth value, highlighting a knowledge gap.

AI-enabled technologies can support and reach youth at scale, anywhere, anytime, with personalised and affordable CMP care.¹¹ However, balancing the potential benefits of digitally-supportive CMP care against risks of harm is important. AI-enabled DHSs are not without risks of harm, such as disinformation,^{23,24} personal data breaches,^{25,26} and the potential to inappropriately de-emphasize or replace clinical care. Addressing these concerns is important because these risks could impact youth’s experiences of CMP care, including feelings of invalidation and stigmatisation,^{3,4} and at the same time limit clinicians’ adoption.²⁷

Co-designing a care ecosystem where digital technologies operate synergistically with clinical pain care, coupled with design efforts to mitigate potential risks of harm, will strengthen person-centred care service delivery.^{11,28} In this context, Discrete Choice Experiments (DCEs) are a widely used method to elicit and measure people’s

preferences for product or intervention attributes, and to inform their co-design.²⁹ Although DCEs have been used to explore people’s preferences for CMP care, most research is limited to older ages, focussed on treatment attributes (e.g., treatment mode) and exclusive of AI-enabled digital coaches.³⁰

To address these knowledge gaps and inform the co-design of a DHS for youth’s CMP care, we employed a mixed-methods research design to identify, validate, and determine the relative importance of attributes and risks of harm of DHSs, including of AI-enabled digital coaches. This study is positioned within a broader research programme, *myPain-health (myPATH)* which aims to develop a digitally enabled adaptive learning system to support quality care of young Australians living with CMP.

Materials and methods

Design

An exploratory three-phase, sequential mixed-methods study was undertaken from April 2023 to November 2024 (Fig. 1).

Phase 1, a qualitative study, adopted a constructivist approach to explore the DHS attributes youth consider when choosing DHSs for their CMP care.³¹ Phase 2, an eDelphi study, evaluated the content validity of these attributes, ranked them by importance and identified risks of harm of digitally-supportive CMP care. Phase 3 used DCEs to explore the preferences for attributes of digital coaches and the risks of harm of digitally-supportive CMP care.

The research was approved by Curtin University’s Human Research Ethics Committee (HRE2022–0588). The overall study is reported in alignment with the Strengthening of Reporting Observational Studies in Epidemiology statement (STROBE³²; Appendix A, p.A2); standards for reporting mixed-methods studies (MMR-RHS³³; Appendix B, p.A4); checklist for reporting research with adolescent and youth engagement³⁴ (Appendix C, p.A6), and the Checklist for Reporting Results of Internet E-Surveys (CHERRIES³⁵; Appendix D, p.A7). Phase-specific reporting checklists are also included: Phase 1: Consolidated criteria for reporting qualitative research (COREQ-32³⁶; Appendix E, p.A11); Phase 2: Guidance on Conducting and Reporting Delphi Studies (CREDES³⁷; Appendix F, p.A13); Phase 3: The Discrete choice experiment Reporting Checklist (DIRECT³⁸; Appendix G, p.A15).

Sampling

Convenience sampling of community-dwelling youth (16–24 years), resident in Australia, was used to create two samples – one for Phases

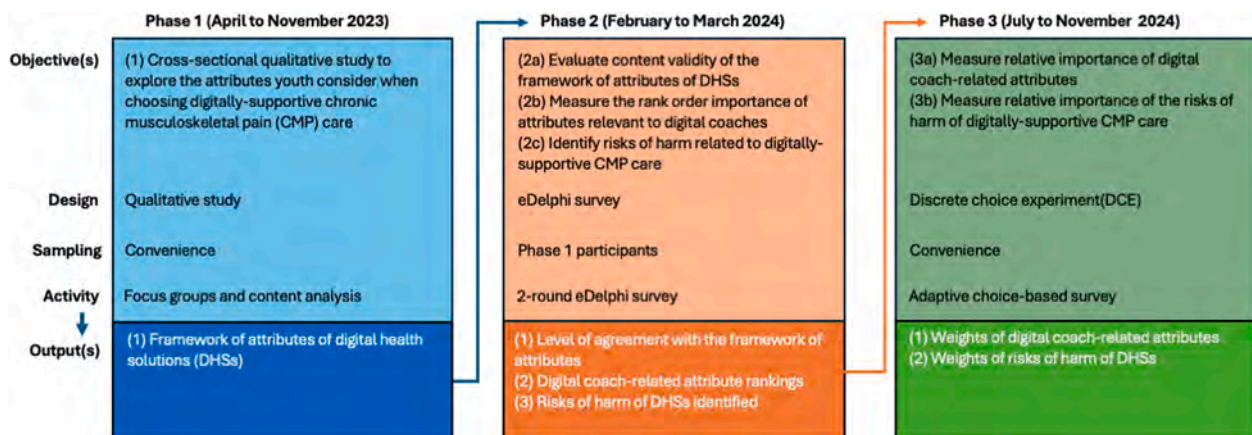


Fig. 1. Overview of the three sequential phases of the research, including objective, design, sampling, activity and output(s), by phase. The arrow leading from one phase to the next shows where the output(s) of each phase informed subsequent phases. A common recruitment strategy was used for the Phase 1/2 and Phase 3 components. Phases 1 and 2 shared the same participants.

1–2, and another for Phase 3. Inclusion criteria were: internet access and current experience of CMP (defined as self-reported CMP experienced for >3 months, continuously or intermittently). Individuals were excluded if they could not speak or understand English or had a history of clinically-diagnosed psychosis. A diagnosis of psychosis was an exclusion criterion based on the unpredictable natural history of psychosis and duty of care considerations. Sampling did not use strata based on socioeconomic position or ethnocultural background, allowing all youth to participate regardless of their background. Where survey responses for any phase failed authenticity criteria, they were excluded as inauthentic (see Appendix D, ‘Survey authenticity criteria’ p.A9–10 for a full description of the survey authenticity criteria applied to the survey data).

Recruitment

Two separate recruitment periods were conducted to enrol two independent samples. The first recruitment period sampled for the Phase 1 and 2 parts of the research. The second recruitment period sampled for the Phase 3 part of the research. For Phase 3, we advertised the study via a range of channels and, also invited those participants who participated in Phases 1 and 2, to consider their interest in participating in Phase 3. The recruitment drives for Phase 1 and Phase 3 shared the same strategy.

To recruit a diverse sample of youth from the broadest range of socioeconomic and ethnocultural backgrounds, key government and non-government organizations across Australia, clinical networks and health professionals with an interest in pain care in youth were contacted via email. Organisations and key stakeholders were asked to share recruitment materials (using email invitation, social media, posters) through their networks. Recruitment materials were also posted on social media platforms (e.g., X, Facebook, Instagram) to increase the reach of the study invitation. These materials guided youth to an online survey (Qualtrics™, Provo, UT, USA), where they were presented with an information statement, requested to provide informed consent, responded to screening questions and completed demographic and clinical profiling questions. Additional details about the recruitment process are reported in separate, related studies.^{4,39} Specific detail about how the online survey was configured to support recruitment across the three study phases, and related responses rates, is reported in the CHERRIES checklist (Appendix D, p.A7–10).

Patient and public involvement

Youth were engaged in this study to ensure that the study design and materials were tailored to, and appropriate for, youth with lived experience of CMP. Appendix C (p.A6) provides additional context about how youth were involved and the overall influence on the study. We will share a summary of findings with the study participants, and we intend to engage youth to help disseminate the research findings.

Phase 1: qualitative study

Data collection

Eight online focus group sessions (60–90 min each) were convened online using Zoom (Video Communications Inc., ver.5, San Jose, California). These were structured using the Nominal Group Technique and guided by a semi-structured schedule (reported in Appendix H, p. A17–18).⁴⁰ One facilitator (JC) led the discussion, while a second (silent) facilitator (AMB) recorded field notes to summarize participants’ ideas into conceptually discrete points. A third researcher (HS) recorded additional field notes. Field notes from each session were used to develop a summary of the discussion, which was shared with the next group to facilitate and extend discussions. Member checking was done in real-time, rather than via distribution of transcripts. An associated manuscript reporting a subset of the qualitative data provides additional detail on data collection.³⁹

Data analysis

Content analysis was used to identify attributes considered by youth when choosing DHSs for their CMP care.⁴¹ This methodology was chosen as it provides a systematic approach to identify discrete codes or patterns within data, and can be applied to distil large volumes of data into a discrete set of categories.^{41,42} As there is limited evidence concerning what attributes of DHSs are important to young people for their CMP care,⁴¹ we used a conventional content analysis approach to inductively identify attributes of DHSs and develop a structured coding framework to capture and organise data related to these attributes. The following taxonomy was adopted to organise and report the study findings:

- *Code* – labels used to describe the meaning of text;
- *Category* – groups of related codes;
- *Attribute* – a category that relates to a characteristic of DHSs (e.g., privacy, accessibility); and
- *Concept group* – higher order categories/attributes underpinned by conceptually-similar categories/attributes.

Focus group recordings were transcribed and checked for accuracy against the recordings by one author (JC). Data were coded inductively, and codes were organised into a coding framework consisting of conceptually discrete categories, with each category representing an attribute of DHSs. One author (SR) independently coded three transcripts using the draft coding framework.

Researchers (JC, AMB, HS, SR) reviewed and revised the coding framework to ensure the attributes were discrete and anchored in the raw data. One author (JC) re-applied the revised coding framework to all transcripts and field notes using NVivo (Lumivero, Denver, CO, USA).

The team (JC, HS, SR, AMB) then reviewed the coding framework against raw data excerpts to refine attribute labels and descriptions, and to organise the attributes into higher-level ‘concept groups’, or clusters of similar attributes. Finally, attributes that were digital coach-related (e.g., related to behavioural support) were identified through independent review of each attribute, discussion and consensus amongst the team. This step to identify digital coach-related attributes, supported the Phase 3 (DCEs). Phase 3 focussed on attributes of AI-enabled digital-coaches specifically, rather than attributes of DHSs more generally. Appendix I (p.A19) details the six-step content analysis approach (that was employed to develop a coding framework, which focused on identifying key attributes of DHSs. Analytical rigour and researcher characteristics and reflexivity statements are reported in Appendix J (p.A25) and Appendix K (p.A26), respectively.

Phase 2: eDelphi study

Data collection

We conducted a single panel, two round e-Delphi survey, powered by the Qualtrics™ (Provo, Utah, USA) survey platform. The preparatory phase of the eDelphi was informed by the focus group activity (study Phase 1), while the output of the eDelphi informed the content of study Phase 3 (see Appendix L, p.A27 for an overview of the steps from e-Delphi preparation to conclusion). All participants in Phase 1 were invited to participate in a 2-round eDelphi survey (Fig. 1), powered by Qualtrics™ (Provo, UT, USA). In Round 1, participants were presented with the attributes identified in Phase 1, organised into concept groups. They were asked to rate their level of agreement with each attribute and with the framework overall on a 5-point Likert scale (1=‘strongly disagree’ to 5=‘strongly agree’). When participants did not agree or strongly agree, a free-text field appeared, inviting them to explain their rating. In Round 2, participants were asked to: (1) re-rate any attributes that did not reach the *a priori* threshold for consensus in Round 1 (see data analysis); (2) rank all digital coach-related attributes in order of importance; and (3) suggest risks of harm (free text).

To minimise respondent attrition and recall bias between eDelphi

survey Rounds 1 and 2, we allowed 1 week for participants to respond to each round. A e-gift card was offered as an honorarium to compensate youth's time if they completed the eDelphi.

Data analysis

For Round 1, response frequencies were calculated to evaluate consensus for each attribute and for the overall framework. Consensus definitions were: 'agreement' as $\geq 80\%$ agree or strongly agree (attribute retained); 'disagreement' as $\geq 80\%$ disagree or strongly disagree (attribute removed); and 'uncertain' as $< 80\%$ agreement or disagreement (attribute requires revision). Free-text responses from Round 1 for any 'uncertain' attributes were used to revise their descriptions. In Round 2, attributes that had been revised following Phase 1 were re-presented to the panel. Mean (SD) rank order and rank correlation (Kendall's W) were calculated to evaluate importance of the digital coach-related attributes and agreement between the panellists, respectively. Free-text responses were content-analysed to identify risks of harm, using a standard content analysis approach.⁴¹ Quantitative data were analysed using SPSS (IBM Corp., Armonk, NY, USA).

Phase 3: discrete choice experiments (DCEs)

Instrument design and data collection

DCEs required participants to make trade-offs between attributes of an AI-enabled digital coach (DCE-1) and risks of harm of a DHS more generally (DCE-2). This involved having participants repeatedly choose between two hypothetical digital coaches (DCE-1) and DHSs (DCE-2) at a time with respect to which one they preferred (including "they are equal"; for an example, see Fig. 2). By making trade-off choices, the relative importance of the digital coach-related attributes, and risks of harm, were calculated as preference weights.

The coaches and DHSs were represented in terms of their attributes and their levels of performance – e.g., for the 'Generates a self-care plan' attribute (Fig. 2A), 'no plan', 'generic plan' and 'personalised'. Harms were framed as the harm concept (e.g. 'Quality of pain care advice & guidance') with performance levels reflecting the level of risk (from low to high; Fig. 2B). Details about the attributes and risks of harms were identified and structured to align with properties for DCE (e.g., preference independence), described in Appendix M (p.A28).

The descriptions for the attributes and risks of harm were informed by Phase 2 outcomes and refined for use in the DCEs through a co-design activity with the myPATH Young Person's Advisory Group (YPAG). We iteratively piloted the DCE survey tools with three youth (including a communications expert) before deployment, to optimise survey validity across: reading level, clarity of survey instruction, clarity of trade-off questions, and syntax. The survey language was simplified following pilot testing to improve readability, comprehension and to minimise survey burden.

The two DCEs were conducted sequentially using the Potentially All Pairwise Rankings of all possible Alternatives (PAPRIKA) method,⁴³ implemented using 1000minds software (www.1000minds.com). After completing DCE-1, participants entered the linked DCE-2. By implementing mathematical properties of additive "multi-attribute value models", including the logical property of transitivity, in real-time, this method arrives at explicit and implicit pairwise rankings of all possible combinations of attributes and their levels. The transitivity property is illustrated via this simple example: if a participant ranks coach 'A' > coach 'B' and coach 'B' > coach 'C', then this implies – by transitivity – that coach 'A' > coach 'C'. Based on each participant's answers to their trade-off questions, PAPRIKA uses quantitative methods based on linear programming to generate weights for the attributes and their levels, representing their relative importance to the participant.

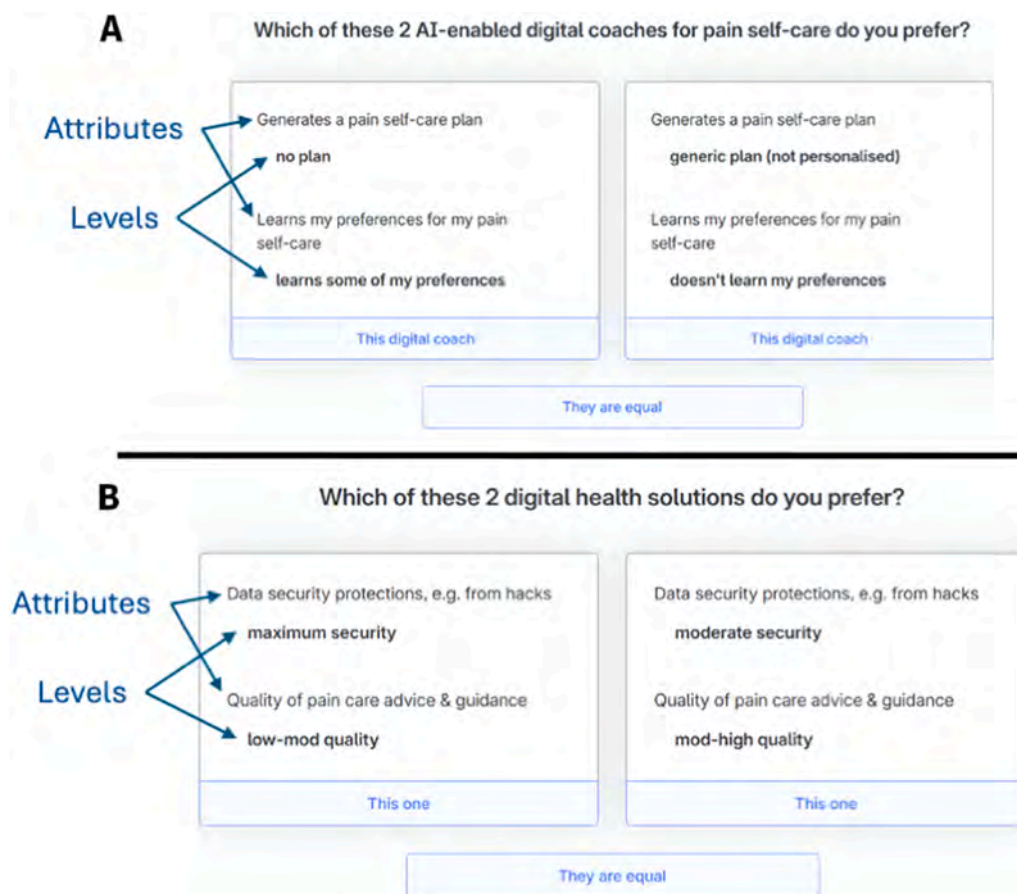


Fig. 2. Examples of trade-off questions for DCE-1 (Panel A) and DCE-2 (Panel B).

To orient youth to the DCE, we prepared a brief online tutorial describing the layout of the DCE and the choice options. To reduce responder burden and to improve survey validity, several functions of the 1000minds.com platform were utilised. Participants could select which attributes and risks of harm were important to them, with up to 6 attributes for DCE-1 and up to 4 for DCE-2 presented in a randomised order. In addition, in DCE-2 participants were asked to nominate (using free text) any risks of harm missing from those presented. At the end of each DCE, two trade-off questions were repeated as a data consistency check.

Data analysis

PAPRIKA determined the participant-level weights of the digital coach-related attributes (DCE-1) and risks of harm (DCE-2), representing their relative importance. Sample means (SD) for each attribute and risks of harm were calculated from participant-level weights. Kendall's W was used to assess agreement on the attributes or risks of harm.

Marginal utility refers to the incremental change in weight from progressing from lower to higher levels of performance on an attribute, and can be decreasing, increasing or constant. To evaluate marginal utility for each attribute, we plotted the weights of that attribute and difference between sample mean weights for sequential levels of performance and visually inspected their marginal utility. Appendix N (p. A29) provides a full description of how marginal utility was calculated in the current study.

Response quality

The 1000minds software allows checks of participants' data validity. Following each DCE, youth were asked to confirm if they agreed (yes/no question) with their personal attribute ranking summaries. To explore genuine engagement with the trade-off questions, we evaluated whether sample mean weights changed when applying established response quality criteria.⁴⁴ Responses that met one or more of the following criteria were considered low quality and excluded in a sub-group analysis: answered two repeated questions inconsistently; completed a trade-off in <1 s or <2 s (median) for all trade-offs; answered all trade-offs the same way (left/right/'they are the same'); or disagreed with their individual-level summary of results.

Results

Table 1 summarises participants' demographic and clinical characteristics across the three phases.

Focus group study (Phase 1)

Twenty-two youth were recruited; one withdrew due to illness and one did not respond. Most participants resided in metropolitan areas (75%) distributed across five Australian states, identified as women (70%), self-reported being born in Australia (95%), self-reported receiving a clinical diagnosis for their CMP condition/s (70%), and identified a concurrent mental health condition (90%).

Framework of attributes of DHSs

Content analysis resulted in a framework of 31 discrete attributes, organised across 10 concept groups. We identified 11 digital coach-related attributes (see Table 2 for list of attributes).

eDelphi study (phase 2)

Round 1 outcomes

All 20 Phase 1 participants (100%) took part in Phase 2. Thirty (97%) attributes reached the threshold for consensus agreement (Table 2). One attribute, 'I value a digital health solution that communicates with other non-

Table 1
Demographic and clinical characteristics of the focus groups, eDelphi and DCE participants.

Characteristic	Phase 1	Phase 2		Phase 3
	Focus groups (N = 20)	eDelphi round 1 panel (N = 20)	eDelphi round 2 panel (N = 19)	DCE-1 participants (N = 41*)
Age (years), mean (SD); range	20.0 (3); 16–24	20.0 (3); 16–24	20.2 (2.6); 16–24	20.8 (2.5); 16–24
Self-reported a concurrent mental health condition (s), n (%)	18 (90)	18 (90)	17 (90)	§
Gender ^{††} , n (%)				
Woman	14 (70)	14 (70)	13 (69)	30 (73)
Man	5 (25)	5 (25)	5 (26)	6 (15)
Non-binary/ third gender, agender	1 (5)	1 (5)	1 (5)	3 (7)
Transgender	2 (5)
Duration of chronic pain (years, median (IQR), range)†	15 (14), 16–24	15 (14), 16–24	15 (14), 16–24	6 (6), 16–24
<i>Clinical profiles, expressed as mean (SD)</i>				
Kessler Psychological Distress scale (K10) score (scale range 10–50)‡	29.6 (7.1)	29.6 (7.1)	29.2 (7.2)	§
Pain Self Efficacy Questionnaire (PSEQ) score (scale range 0–60)¶	36.0 (12.3)	36.0 (12.3)	36.5 (12.4)	28.6 (12.8)
Brief Pain Inventory (BPI) pain severity subscale score (score range 0–10)	5.0 (2.1)	5.0 (2.1)	4.9 (2.2)	4.9 (1.5)
Brief Pain Inventory (BPI) pain interference subscale score (score range 0–10)**	4.6 (2.6)	4.6 (2.6)	4.7 (2.2)	5.8 (2.0)
Brief Pain Catastrophizing (BriefPCS) chronic scale score (score range 0–16)††	9.0 (4.3)	9.0 (4.3)	8.9 (4.4)	§

* N=40 completed DCE-2 (risks of harm of DHSs).

^ Young people were asked to respond 'yes' or 'no' to, "Over the past 6 months, has your chronic pain impacted how you feel within yourself (i.e. your emotional, psychological or mental health wellbeing)? For example, does your pain impact your mood, or feelings of distress or anxiety?" and "Has a health professional provided you with a diagnosis about you psychological or emotional health (e.g.: low mood, anxiety)?"

^^ Using the 2011 Australian Bureau of Statistics standard for gender, defined as social and cultural differences in identity, expression and experience as a man, woman or non-binary person (<http://www.abs.gov.au/statistics/standards/standard-sex-gender-variations-sex-characteristics-and-sexual-orientation-variables/latest-release>).

† Both primary and secondary CMP (aligned with ICD-11 classifications) were included.

‡ K10⁶² higher scores reflect greater psychological distress. Scores <20 = are likely to be well, scores 20–24 = are likely to have a mild mental disorder, scores 25–29 = are likely to have moderate mental disorder, and scores ≥30 = are likely to have a severe mental disorder. Scores are calculated as the sum over 10 items with ratings on a 1–10 scale, where "0" represents "none of the time" and "10" represents "all of the time".

§ Not collected in Phase 3 to minimise participant burden.

¶ PSEQ⁶³ higher scores reflect stronger self-efficacy beliefs. Scores are calculated as the sum over 10 items rated on a numeric rating 0–6 scale, where "0" represents "not at all confident" and "6" represents "completely confident."

|| BPI-pain severity⁶⁴ a higher score reflects greater pain severity and is calculated as the mean score over 4 items (average, worst, least pain over the past week and pain right now) rated on a 0–10 numeric rating scale, where "0" represents no pain and "10" pain as bad as you can imagine.

** BPI-pain interference⁶⁴ higher scores reflect greater pain interference with activities of daily living based on the patient's self-reported BPI scores for the items measuring interference. The interference questions are rated on a 0–10 numeric rating scale, where 0 represents "Does not interfere" and 10 represents "Completely interferes". The interference subscale is an average of the seven interference questions.

†† Brief pain catastrophizing scale⁶⁵ (BriefPCS-chronic) score (range 0–16). Higher scores reflect high levels of catastrophic thoughts. Scores are calculated as the sum over 4 items rated on a 5-point Likert scale ranging from 0 to 4, where “0” represents “never” and “4” represents “always”.

health apps that help me manage my pain... did not reach consensus (70% agree or strongly agree) and was revised for re-assessment in Round 2. Consensus agreement with the overall framework was achieved (30% agree and 70% strongly agree).

Round 2 outcomes

At the end of Round 2 (n=19; 95% response rate), all 31 (100%) attributes reached the consensus threshold for agreement (Table 2). Agreement across rankings of the 11 coach-related attributes was low ($W=0.113$, $\chi^2(21.4) = 10$, $p=0.018$), suggesting that different youth prioritise different attributes. Therefore, all 11 attributes were appropriate for inclusion in the digital coach-related DCE-1. Analysis of free text responses generated six risks of harm (Table 3).

Discrete choice experiments (phase 3)

Fifty-two youth were recruited; 11 did not complete DCE-1 and a further one young person did not proceed to complete DCE-2. Thus, 41 and 40 youth completed DCE-1 and DCE-2, respectively, of whom 88% were born in Australia. The participant flow from enrolment to analysis in DCE-1 and DCE-2, is depicted in Fig. 3.

Digital coach-related attributes (DCE-1)

Preference weights. Table 4 shows the sample mean preference weights for the digital coach-related attributes presented to youth in DCE-1. The three most important digital coach-related attributes contributed to almost half (46.6%) of weight that youth placed on the 11 digital coach-related attributes, including (mean weight[SD]): ‘Generates a pain self-care plan’ (19.6[14.5]); ‘Learns my preferences for pain self-care’ (15.9[12.9]); and ‘Supports my healthcare visits’ (11.1[12.4]). Consistency between the preference weights of the attributes was low ($W = 0.161$, $\chi^2(72.4) = 11$, $p = <0.001$), suggesting youth place different importance on the coach-related attributes.

Marginal utility. With each higher level of performance of a coach-related attribute, the value youth placed on performance diminished, shown by decreasing differences in mean weight between sequential levels (i.e., diminishing marginal utility). This is visually represented in Table 4 by the horizontal bar plots, and can be interpreted by the decreasing difference between adjacent horizontal bars in the plots. This suggests that as the performance level increases, each level of additional improvement on the attributes provides less value to youth. However, for the attribute ‘My coach’s personality’, the difference in mean weight between sequential levels of performance remained largely constant. Marginal utility could not be interpreted for four attributes, since they were each defined on two levels only: ‘Delivers fast-acting pain care’, ‘Helps me to track my goals’, ‘Range of pain care support it provides’ and ‘Alerts me when things might go wrong’. Appendix O (p.A30) provides further detail about marginal utility outcomes. Appendix O also provides a visual depiction of the relationship between the weights and marginal utilities of the coach-related attributes by plotting the difference in mean weights between sequential levels of performance for each attribute.

Risks of harm (DCE-2)

Preference weights. Table 4 shows the sample mean preference weights for the risks of harm presented to youth in DCE-2. Three risks of harm contributed over half of the weight (57.7%) attached to risks of harm (mean weight[SD]): ‘Quality of pain care advice & guidance’ (31.8[17.3]);

‘Information being consistent with advice from my healthcare provider team’ (25.8[17.5]); and ‘Control over whom I share my data with’ (12.3[17.6]). Consistency on the weights of the risks of harm was low ($W = 0.267$, $\chi^2(53.4) = 5$, $p = <0.001$), suggesting that different youth have different risk preferences.

Marginal utility. As risk level decreased through a higher level of performance, the value youth placed on performance diminished, shown by decreasing differences in mean weight between sequential levels (i.e., diminishing marginal utility). This is visually represented in Table 4, by the horizontal bar plots, and can be interpreted by the decreasing difference between adjacent horizontal bars in the plots. This suggests that as the performance level increases (decreasing risk), each level of additional improvement on the potential risk provides less value to youth. However, for the risk ‘Potential for reliance on technology,’ the difference in mean weight between sequential levels of performance remained largely constant. The marginal utility function for ‘Safety check’ could not be interpreted because the attribute was only defined on two levels. Appendix O (p.A30) provides an explanation and visual depiction of the relationship between the weights and marginal utilities of the risk of harm attributes.

Response quality

Almost all participants agreed with their individual-level weights for DCE-1 (n=40; 98%) and DCE-2 (n=38; 95%), confirming response validity. Excluding the low-quality responses did not change the preference weight rank-order of the coach-related attributes or the top two risks of harm. However, the preference weight order of the third to least risks of harm changed - this is reported Appendix P, (p.A33).

Discussion

Main findings

To the authors’ knowledge, this is the first study to explore what youth experiencing CMP value in digitally-supportive CMP care, including their perceived risks of harm and preferences for AI-enabled digital coaches. The study findings contribute unique evidence, from the perspective of CMP care for youth, to a wider body of literature on digitally-supportive care for other chronic conditions,^{18,21,26,45} and for pain care in younger groups.^{46–48} Youth may consider up to 31 attributes and six potential risks of harm when choosing DHSs to support their CMP care. On average, a subset of these attributes was most important to youth choosing AI-enabled digital coaches, and in considering related risks of harms. This subset is likely critical to informing the co-design of person-centred DHSs that includes an AI-enabled digital coach. Youth’s preferences varied, likely reflecting their diverse experiences with CMP, consistent with evidence,^{3,4} and underscoring the need for personalisation of digitally-supportive care.

Strengths and limitations

A strength of the current study is the exploratory, sequential mixed-methods design, enabling explicit integration of youth lived CMP experience perspectives at each phase, aligning with patient and public involvement best practice and principles.^{22,34} Further, the sample reflects diversity in demographic and clinical pain profiles,¹¹ including the common experience of mental health comorbidities,³ enhancing confidence in the transferability of the findings to other contexts. Nonetheless, the findings should be considered in the context of potentially important limitations. The sample size was modest and not fully representative of diversity in youth living with CMP from culturally or Australian geographically diverse backgrounds; important considerations for pain care and research.⁴⁹ Consistent with other CMP research,

most of the sample identified as women, reflecting the higher prevalence of CMP in girls and women.^{1,50} Participants who identified as men or non-binary were under-represented. Despite best efforts to define conceptually discrete attributes for DCE-1, the authors cannot rule-out that some attributes may be interdependent, which may have confounded the preference weights. Variability of lived experience of CMP may account for the wide heterogeneity in attribute weights, and a larger sample may increase precision in the estimates.

Attributes of digital health solutions

Attributes concerning the functionality of DHSs in general align with evidence for the behavioural, emotional and social needs of youth experiencing CMP,^{3,4,51} e.g., ‘helps me to remember things...’; ‘supports my mood when I need it’; ‘helps me to communicate with my social network’. These findings signal that youth prefer technologies that help them live well and support their CMP care in ways that are meaningful, consistent with their preferences for pain care interventions more generally.³⁹ Valued attributes also encompassed preferences for accessibility, pleasant and uncomplicated user experience and affordability (e.g., *inclusivity, device settings, cost*). These accessibility attributes are consistent with the digital determinants of health, and resonate with preferences of youth living with other chronic conditions (e.g., diabetes, mental ill-health).^{18,52}

There are important differences between the current study’s findings and prior studies on other chronic health conditions. For example, this study identified that DHSs could help youth with CMP navigate a health system. This was not the case for youth accessing diabetes or cancer care, the difference possibly reflecting that, compared to CMP, care and transition pathways are better understood and established for diabetes and cancer.^{53,54} The findings also contrast with evidence from other chronic conditions regarding specific components of care. For example, digitally-supportive diabetes care strongly features physiologic targets (e.g., glycaemic control), whereas CMP care has no defined biomarkers, instead focusing on pain control and functional restoration.^{11,55}

Although there is potential for use of AI-enabled self-care, little is known about youth’s preferences for such technologies, particularly in those experiencing CMP. The findings highlight that youth valued an AI-enabled digital coach that could respond to their needs and preferences. Providing personalised, supportive pain care, reinforced through guided self-care, can help empower youth in managing their CMP. Digital coaches co-designed with these attributes are likely to be more desirable to, and adopted by youth with CMP, providing actionable help ‘in the moment’, and beyond.¹¹ Notwithstanding youth’s desire for positive healthcare encounters, ‘my coach’s personality’ was the least valued coach-related attribute. This finding may suggest that youth are already familiar with AI technology, making this attribute less valued, or suggest that they already have clinical care or are unfamiliar with how a digital

Table 2

Attributes of digital health solutions (DHSs) identified from Phase 1 through content analysis, their level of agreement following eDelphi Round 1 and Round 2, and the mean rank of the digital coach attributes.

Attributes by concept group	Round 1 (N=20)						Round 2 (N=19)						Mean (SD) rank*
	Level of agreement, N (%)						Level of agreement, N (%)						
Each attribute phrased as: “I value a digital health solution that...”	Strongly disagree	Dis-agree	Unsure	Agree	Strongly agree	Met consensus at end of Round 1	Strongly disagree	Dis-agree	Unsure	Agree	Strongly agree	Met consensus at end of Round 2	Digital coach attribute
Credibility													
...is credible and trustworthy, so I don't have to verify the information myself.	0 (0)	0 (0)	0 (0)	6 (30)	14 (70)	✓
Inclusivity													
...offers different interaction options according to my preferences and needs.	0 (0)	0 (0)	0 (0)	8 (40)	12 (60)	✓
...involved young people with lived experience of chronic musculoskeletal pain in its development.	0 (0)	0 (0)	0 (0)	9 (45)	11 (55)	✓
Personalised pain management													
...creates a personalised plan to help me achieve my goals. †	0 (0)	1 (5)	0 (0)	9 (45)	10 (50)	✓	5-3 (3-1)
...helps me to track my goals. †	0 (0)	1 (5)	1 (5)	7 (35)	11 (55)	✓	7-2 (3-2)
...recommends pain care options that have an immediate effect. †	0 (0)	0 (0)	1 (5)	9 (45)	10 (50)	✓	5-1 (2-3)
...helps me to make sense of my condition(s) or diagnosis.	0 (0)	0 (0)	1 (5)	5 (25)	14 (70)	✓
...helps me to make sense of my pain care options.	0 (0)	0 (0)	0 (0)	9 (45)	11 (55)	✓
...learns my preferences for my pain management. †	0 (0)	0 (0)	0 (0)	9 (45)	11 (55)	✓	4-9 (3-3)
...generates pain care recommendations that are useful to	0 (0)	0 (0)	1 (5)	9 (45)	10 (50)	✓	4-2 (2-4)

(continued on next page)

Table 2 (continued)

me, even if I don't have a clear-cut diagnosis. †																
Coaching																
...helps me to remember things I need to do for my self-care. †	0 (0)	0 (0)	0 (0)	11 (55)	9 (45)	✓	6-7 (2-7)	
...motivates me to stick to my pain care plan. †	0 (0)	0 (0)	2 (10)	14 (70)	4 (20)	✓	6-6 (4-0)	
...helps me to predict when things might go wrong. †	0 (0)	1 (5)	1 (5)	8 (40)	10 (50)	✓	6-5 (2-4)	
...supports my mood when I need it. †	0 (0)	0 (0)	1 (5)	6 (30)	13 (65)	✓	7-8 (2-8)	
...engages me in a way that feels natural. †	0 (0)	0 (0)	1 (5)	8 (40)	11 (55)	✓	6-4 (3-6)	
Data sharing																
...communicates with other health-related information systems or apps so that my digital health profile is complete and ready to support me, or others, in my care team.	0 (0)	0 (0)	0 (0)	7 (35)	13 (65)	✓	
...gives me the option to connect with other apps, without sharing my data with those other apps. ‡	0 (0)	0 (0)	6 (30)	9 (45)	5 (25)	✗	0 (0)	1 (5)	1 (5)	11 (58)	6 (32)	✓	
...allows me to share my clinical history with healthcare providers so I don't have to repeat myself.	0 (0)	0 (0)	0 (0)	6 (30)	14 (70)	✓	
...allows my healthcare team to connect with me between appointments so I can be updated with real-time clinical advice.	0 (0)	0 (0)	0 (0)	5 (25)	15 (75)	✓	
Navigating health systems																
...helps me to navigate my health care system.	0 (0)	0 (0)	0 (0)	9 (45)	11 (55)	✓										
...helps me to navigate clinical encounters so I can get the most value out of them. †	0 (0)	0 (0)	0 (0)	6 (30)	14 (70)	✓	5-3 (3-4)	
Community																
...connects me with a network of other young people experiencing chronic pain.	0 (0)	0 (0)	3 (15)	13 (65)	4 (20)	✓	
...helps me to communicate with my social network.	0 (0)	0 (0)	1 (5)	15 (75)	4 (20)	✓	
Device settings																
...allows me to input data or search for information in different ways.	0 (0)	0 (0)	0 (0)	12 (60)	8 (40)	✓	
...lets me create shortcuts to the features I find useful, so I can access them quickly.	0 (0)	0 (0)	0 (0)	5 (25)	15 (75)	✓	
...is convenient so that I can use it wherever, whenever.	0 (0)	0 (0)	0 (0)	5 (25)	15 (75)	✓	
...allows me to customise content and notifications.	0 (0)	0 (0)	0 (0)	6 (30)	14 (70)	✓	
...has a pleasing look and feel and is easy to use.	0 (0)	0 (0)	0 (0)	4 (20)	16 (80)	✓	
...allows me to download my data.	0 (0)	0 (0)	0 (0)	8 (40)	12 (60)	✓	
Data security and privacy																
...protects my personal data (security) and gives me control over how it is shared (privacy).	0 (0)	0 (0)	0 (0)	2 (10)	18 (90)	✓	
Cost																
...is free or low cost to use.	0 (0)	0 (0)	0 (0)	3 (15)	17 (85)	✓	

* Attributes with lower mean ranks are higher ranked.

† Denotes a coach-related attribute.

‡ Content analysis of free text responses for this attribute indicated that youth wanted the description to reflect greater control and safety over their data. To reassess level of agreement, this attribute was revised from "I value a digital health solution that communicates with other non-health apps that help me manage my pain..." to "I value a digital health solution that gives me the option to connect with other apps, without sharing my data with those other apps..." and was re-presented to youth in Round 2.

coach might work in practice. It may also reflect how digital coaches were framed in the DCE-1, as complimentary to clinical care, potentially reducing the perceived value-add. Alternatively, this attribute may be valued differently by sub-groups of youth. For example, the preliminary subgroup analysis by gender, suggests that men and women share similar preferences, but for only the two most preferred coach-related

attributes and risks of harm (results of the preliminary analysis are reported in Appendix Q, p.A34). A larger sample would increase confidence in estimates of sub-group specific preferences and better enable exploration of associations between weights and clinical/demographic characteristics.

Table 3
Potential risks of harm of digital health solutions identified following eDelphi round 2.

Potential risks of harm of digital health solutions
1. Generates information that is misinterpreted by me, e.g., a digital coach does not check my understanding of the potential risks of an intervention.
2. Replaces my healthcare team, e.g., I become dependent on the technology to gather information, prepare a care plan or interpret symptoms I am experiencing, rather than seeking health professional advice when I might need it.
3. Shares my personal data without my consent. e.g., to the public.
4. Stores my personal data insecurely, such that it is vulnerable to data-hacks or leaks.
5. Recommends pain self-care plans that conflict with advice from my healthcare team.
6. Generates incomplete, inaccurate or outdated pain care recommendations. Artificial intelligence, for example, might formulate decisions from an incomplete data set, causing it to generate low-quality recommendations.

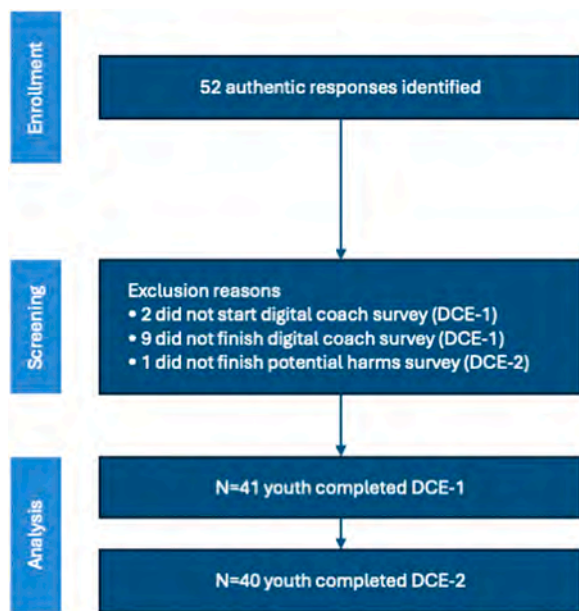


Fig. 3. Phase 3 participant flow from enrolment in DCE-1 through to screening and analysis, including those who responded to DCE-2.

Risks of harm

The risks of harm from DHSs identified by youth included poor information quality and information consistency, and autonomy over their personal health data (e.g., *data security, control*). These findings are consistent with harms reported by youth experiencing other chronic conditions.²⁶ Youth were most concerned about ‘*Quality of pain care advice*’, which may reflect past experiences of receiving conflicting information from their healthcare team, or negative interactions during clinical encounters.³ In this respect, AI-enabled DHSs embedded within a health service could help to improve the quality, consistency and personalisation of both clinical care and self-care.^{11,28} Here, clinical and digital CMP care could work synergistically to support youth with quality, consistent and tailored pain care advice, with the added benefit of mitigating their perceived risk about *becoming reliant on DHSs*.^{11,28} Technical capabilities that build trust in DHSs, such as data privacy and security technologies that ensure appropriate ‘guard rails’ are important co-design considerations to mitigate risks of harm. Communicating what, where, when and how a DHS supports clinical care (e.g., role of an AI-enabled digital coach) and ensures privacy and security protections, is likely to support youth’s engagement with, and sustained adoption of digitally-supportive care. Contrasting with other work, youth in the current study did not identify the ‘digital divide’ as a potential harm.⁵⁶ This finding may reflect the sample’s familiarity with, and access to, digital technology. Nonetheless, clinical service models that integrate digital support must be co-designed with genuine efforts to address care needs and to mitigate digital inequities.⁵²

Implications

The attributes and their weights identified offer a starting point to inform the co-design of DHSs that can support youth’s CMP self- and clinical co-care. For example, in a health technology assessment framework – which offers a structured approach to evaluation – the attributes and risks of harm identified could be used to model youth’s and other key decision-makers’ willingness to pay for, or use, different configurations of AI-enabled digital coaches. This information could help generate value-add information about potential ‘return on investment’; an important step towards informing value-based health services and transparent, system- level evidence-based decision-making.^{57,58} Using adaptive trials designs to test time-sensitive, tailored care intervention strategies and delivery mechanisms could identify how different features of a DHS for youth may benefit their pain experiences, care journeys, and health outcomes.^{59–61}

Conclusion

In conclusion, this study identified that youth consider a range of attributes of DHSs when choosing digitally-supported CMP care. A subset of attributes drive their preferences for AI-enabled digital coaches and their concerns about related risks of harm. These attributes are important to incorporate into the co-design of digitally-enabled CMP care services to augment clinical pain care in a way that is appealing to young people, and if successful, inform scalable, accessible, safe, timely, affordable and tailored support for youth living with CMP.

CRediT authorship contribution statement

Conceptualization; JC, HS, AMB, Data curation; JC, HS, AMB, Formal analysis; JC, HS, SR, PH, AMB, Funding acquisition; JC, HS, AJS, SML, PBO, JNS, AMB, Investigation; JC, HS, SR, AMB, Methodology; JC, HS, SR, PH, AJS, SML, PBO, BT, JNS, AMB, Project administration; JC, HS, SR, AMB, Supervision; HS, SR, AMB, Roles/Writing - original draft; JC, HS, SR, PH, AMB, Writing - review and editing; JC, HS, SR, PH, AJS, SML, PBO, BT, JNS, AMB.

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Table 4

Sample mean preference weights (%) of the 11 coach-related attributes and six risks of harm in discrete choice experiment (DCE)-1 and DCE-2, respectively.

Coach-related attribute [% of the sample that selected the attribute for the DCE*]	Sample mean weight (SD) (N=41) ‡	Visual depiction of relative weights for each performance level, by attributes	Risks of harm [% of the sample that selected the attribute for the DCE†]	Sample mean weight (SD) (N=40) ‡	Visual depiction of relative weight by performance level relevant to each risk of harm§
Levels (lowest to highest performance)					
Generates a pain self-care plan [73.2]					
1 No plan	0.0 (0.0)		Quality of pain care advice & guidance [85.0]		
2¶ [Between level 1 and 3]	5.0 (4.4)		1 Low quality	0.0 (0.0)	
3 Generic plan (not personalised)	10.0 (8.1)		2¶ [Between level 1 and 3]	10.9 (6.0)	
4¶ [Between level 3 and 5]	14.8 (11.2)		3 Moderate quality	20.2 (10.9)	
5 Personalised plan	19.6 (14.5)		4¶ [Between level 3 and 5]	26.8 (14.3)	
Learns my preferences for my pain self-care [78.0]					
1 Doesn't learn my preferences	0.0 (0.0)		5 High quality	31.8 (17.3)	
2¶ [Between level 1 and 3]	5.7 (5.4)		Information being consistent with advice from my healthcare team [77.5]		
3 Learns some of my preferences	10.2 (9.2)		1 Not consistent	0.0 (0.0)	
4¶ [Between level 3 and 5]	13.4 (11.3)		2¶ [Between level 1 and 3]	7.6 (5.6)	
5 Learns most of my preferences	15.9 (12.9)		3 Somewhat consistent	14.6 (10.2)	
Supports my healthcare visits [56.1]					
1 No support	0.0 (0.0)		4¶ [Between level 3 and 5]	20.6 (13.8)	
2¶ [Between level 1 and 3]	2.9 (3.5)		5 Very consistent	25.8 (17.5)	
3 Generic support (not personalised)	5.7 (6.7)		Data security protections [52.5]		
4¶ [Between level 3 and 5]	8.4 (9.4)		1 Minimum security	0.0 (0.0)	
5 Personalised support	11.1 (12.4)		2¶ [Between level 1 and 3]	4.9 (5.5)	
Helps me remember things [61.0]					
1 No prompting	0.0 (0.0)		3 Moderate security	9.1 (10.2)	
2¶ [Between level 1 and 3]	3.6 (4.0)		4¶ [Between level 3 and 5]	12.2 (14.1)	
3 Some prompting	6.4 (7.0)		5 Maximum security	14.8 (17.6)	
4¶ [Between level 3 and 5]	8.1 (8.6)		Control over who I share my data with [55.0]		
5 A lot of prompting	9.2 (9.6)		1 Minimum control	0.0 (0.0)	
Provides mind & mood support [41.5]					
1 No support	0.0 (0.0)		2¶ [Between level 1 and 3]	3.7 (5.2)	
2¶ [Between level 1 and 3]	3.1 (4.4)		3 Moderate control	7.1 (9.4)	
3 Some support	5.6 (7.8)		4¶ [Between level 3 and 5]	9.9 (12.2)	
4¶ [Between level 3 and 5]	7.4 (10.0)		5 Maximum control	12.3 (14.5)	
5 A lot of support	8.7 (11.7)		Safety check, to make sure I understand information provided [52.5] 		
Delivers fast-acting pain care [51.2] 					
1 No	0.0 (0.0)		1 No	0.0 (0.0)	
2 Yes	8.2 (10.1)		2 Yes	8.0 (13.6)	
Helps me to track my goals [43.9] 					
1 No goal tracking	0.0 (0.0)		Potential for reliance on technology [50.0]		
2 Helps track my goals	7.1 (10.2)		1 High chance	0.0 (0.0)	
Range of pain care support it provides [24.4] **					
1 Narrow (specific to my diagnosis)	2.2 (5.3)		2¶ [Between level 1 and 3]	2.1 (4.3)	
2 Broad (support for all MSK pain)	3.8 (7.1)		3 Moderate chance	3.9 (7.1)	
Alerts me when things might go wrong [36.6] 					
1 No alert	0.0 (0.0)		4¶ [Between level 3 and 5]	5.5 (8.6)	
2 Provides an alert	5.5 (8.5)		5 Low chance	7.3 (10.4)	
Gives me motivational support [34.1]					
1 No support	0.0 (0.0)		My coach's personality, i.e. human-ness [22.0]		
2¶ [Between level 1 and 3]	1.5 (3.0)		1 Fully robotic	0.0 (0.0)	
3 Some support	2.9 (5.2)		2¶ [Between level 1 and 3]	0.9 (2.3)	
4¶ [Between level 3 and 5]	4.0 (7.0)		3 Mix of robotic and human	1.8 (4.3)	
5 A lot of support	5.2 (8.9)		4¶ [Between level 3 and 5]	2.6 (6.3)	
My coach's personality, i.e. human-ness [22.0]					
1 Fully robotic	0.0 (0.0)		5 Fully human-like	3.5 (8.5)	
2¶ [Between level 1 and 3]	0.9 (2.3)				
3 Mix of robotic and human	1.8 (4.3)				
4¶ [Between level 3 and 5]	2.6 (6.3)				
5 Fully human-like	3.5 (8.5)				

* Represents the proportion of the sample who selected the attribute in discrete choice experiment-1 (DCE-1) from the 11 coach-related attributes.

† Represents the proportion of the sample who selected the attribute in discrete choice experiment-2 (DCE-2) from the six risks of harm.

‡ The weights of the highest level of performance for each attribute sum to 100% and represent their relative preference.

§ Horizontal bar graphs reflect the weight on each level of performance of an attribute (DCE-1) or risk of harm (DCE-2). The consistency of the difference in mean weight between sequential levels (or one bar, to the next) for a given attribute provides a visual depiction of the attribute's marginal utility function (see Appendix O for more detail).

¶ The point estimate of this level was interpolated by applying a Bézier curve to the mean weights of the 1st, 3rd and 5th levels of the attribute, powered by 1000minds.
 || Attributes or risks of harm with only two levels do not provide enough information to judge increasing, decreasing or constant marginal utility - an attribute must have at least 4 levels to calculate three data points representing the weight difference between levels 1–2, 2–3, and 3–4.

** Young people were able to select which level was the 'worst' and which was the 'best' (i.e., self-explicated). The overall mean weight of this attribute is the sum of the weight of its two levels ($3.8 + 2.2 = 6.0\%$).

Statement of financial disclosure

JC declares travel support from the Auckland Medical Research Fund to attend project meetings in Perth and the Australian Pain Society, Annual Scientific Meeting.

HS declares research grant income, unrelated to the current submission, paid to her institution in the 36 months prior to submission of the current paper, from the following agencies: Government of Australia (Health Professional Pain Education; Health Professional Arthritis Education; Endometriosis), AO Alliance, Asia Pacific League of Associations for Rheumatology, Australian Rheumatology Association, Pan American League of Associations for Rheumatology, World Federation of Chiropractic, Western Australian Government Department of Health Grant, Arthritis Australia. **HS** also declares travel and accommodation support from the International Association for the Study of Pain, Australian Pain Society, Australian Physiotherapy Association and Australian and New Zealand College of Anaesthetists (Faculty of Pain Medicine) for invited presentations at scientific meetings and technical meetings.

SML declares employment as a specialist pain medicine physician treating children and youth within a government-owned health service. She also declares research grant income, unrelated to the current submission, paid to her institution or other universities in the 36 months prior to submission of the current paper, from the following agencies: the Australian Pain Society, the Society of Paediatric Anaesthetists of New Zealand and Australia, the Australian Government Medical Research Future Fund, and the Network of European Funding for Neuroscience Research. She also declares pro bono work for the following organisations: the NSW Health Agency for Clinical Innovation Pain Management Network, the Australian Pain Society, the electronic Persistent Pain Outcomes Collaboration, and the Australian and New Zealand College of Anaesthetists (ANZCA) and its Faculty of Pain Medicine (FPM). She declares travel and accommodation support to attend various ANZCA and FPM governance meetings.

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PBO receives speaker's fees for conducting multi-disciplinary clinical workshops on person-centred care for people with musculoskeletal pain.

AMB declares research grant income, unrelated to the current submission, paid to his institution in the 36 months prior to submission of the current paper, from the following agencies: Government of Australia (Health Professional Pain Education; Health Professional Arthritis Education), AO Alliance, Asia Pacific League of Associations for Rheumatology, Australian Rheumatology Association, Pan American League of Associations for Rheumatology, World Federation of Chiropractic, Western Australian Government Department of Health Grant, Arthritis Australia and Arthritis and Osteoporosis Western Australia. **AMB** also declares consulting fees paid by the World Health Organization, an honorarium paid by the American College of Rheumatology, and travel support to attend technical and scientific meetings from the World Health Organization, University of Otago, World Federation of Chiropractic and Australian Rheumatology Association. **AMB** is an unpaid and voluntary member of the International Coordinating Council of the Global Alliance for Musculoskeletal Health.

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Declaration of Generative AI and AI-assisted technologies in the writing process

Not applicable.

Declaration of Competing Interest

JC, HS, SR, PH, AJS, PBO, BT, JNS and AMB report no conflict of interest. **SML** reports that as a clinician and member of government and non-government organizations across Australia, she was involved in dissemination of study information in the recruitment phase.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.jpain.2026.106257](https://doi.org/10.1016/j.jpain.2026.106257).

Data availability

All data collected for this study are included in the manuscript and supplemental files.

References

- Chambers CT, Dol J, Tutelman PR, et al. The prevalence of chronic pain in children and adolescents: a systematic review update and meta-analysis. *PAIN*. 2024;165(10):2215–2234. <https://doi.org/10.1097/j.pain.0000000000003267>.
- Murray CB, de la Vega R, Murphy LK, Kashikar-Zuck S, Palermo TM. The prevalence of chronic pain in young adults: a systematic review and meta-analysis. *PAIN*. 2022;163(9):e972–e984. <https://doi.org/10.1097/j.pain.0000000000002541>.
- Klem NR, Slater H, Rowbotham S, et al. Lived and care experiences of young people with chronic musculoskeletal pain and mental health conditions. A systematic review with qualitative evidence synthesis. *PAIN*. 2025;166(4):732–754. <https://doi.org/10.1097/j.pain.0000000000003407>.
- Klem NR, Briggs AM, Rowbotham S, et al. "It's kind of just like a never-ending cycle": young people's experiences of co-existing chronic musculoskeletal pain and mental health conditions. *J Pain*. 2025;32, 105412. <https://doi.org/10.1016/j.jpain.2025.105412>.
- Berkovic D, Briggs AM, Ayton D, Parker C, Ackerman I. Arthritis-related work outcomes experienced by younger to middle-aged adults: a systematic review. *Occup Environ Med*. 2020;78(4):225–236. <https://doi.org/10.1136/oemed-2020-106640>.
- Berkovic D, Ayton D, Briggs AM, Ackerman IN. "I Would be More of a Liability than an Asset": navigating the workplace as a younger person with arthritis. *J Occup Rehabil*. 2020;30(1):125–134. <https://doi.org/10.1007/s10926-019-09853-2>.
- O'Sullivan PB, Beales DJ, Smith AJ, Straker LM. Low back pain in 17 year olds has substantial impact and represents an important public health disorder: a cross-sectional study. *BMC Public Health*. 2012;12:100. <https://doi.org/10.1186/1471-2458-12-100>.
- Dudeney J, Aaron RV, Hathway T, et al. Anxiety and depression in youth with chronic pain: a systematic review and meta-analysis. *JAMA Pediatr*. 2024;178(11):1114–1123. <https://doi.org/10.1001/jamapediatrics.2024.3039>.
- Australian Bureau of Statistics. National study of mental health and wellbeing. 2022. Accessed December 11, 2025. (<https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-wellbeing/latest-release>).

10. Deloitte Access Economics. *The cost of pain in Australia*. Canberra: 2019. Accessed December 19, 2025. Available at (<https://www.deloitte.com/au/en/services/economics/analysis/cost-pain-australia.html>).
11. Slater H, Waller R, Briggs AM, Lord SM, Smith AJ. Characterizing phenotypes and clinical and health utilization associations of young people with chronic pain: latent class analysis using the electronic Persistent Pain Outcomes Collaboration database. *PAIN*. 2025;166(1):67–86. <https://doi.org/10.1097/j.pain.0000000000003326>.
12. Rigby E, Hagell A, Davis M, Gleeson H, Mathews G, Turner G. Getting health services right for 16–25 year-olds. *Arch Dis Child*. 2021;106(1):9–13. <https://doi.org/10.1136/archdischild-2019-318648>.
13. Klem NR, Briggs AM, Slater H. Response to Nufi. letter to the editor, "From fragmented services to whole-person care: Rethinking young people's pain-mental health management". *J Pain*. 2025;37, 105574. <https://doi.org/10.1016/j.jpain.2025.105574>.
14. Feinstein AB, Brown K, Dunn AL, et al. Where do we start? Health care transition in adolescents and young adults with chronic primary pain. *PAIN*. 2025;166(2): 236–242. <https://doi.org/10.1097/j.pain.0000000000003324>.
15. Slater H, Jordan JE, Chua J, Schütze R, Wark JD, Briggs AM. Young people's experiences of persistent musculoskeletal pain, needs, gaps and perceptions about the role of digital technologies to support their co-care: a qualitative study. *BMJ Open*. 2016;6(12), e014007. <https://doi.org/10.1136/bmjopen-2016-014007>.
16. Mason KJ, Jordan KP, Bailey J, et al. Trends of musculoskeletal pain in children and young people consulting primary care: an electronic primary health care record study. *BMC Pediatr*. 2025;25(1):961. <https://doi.org/10.1186/s12887-025-06296-y>.
17. Mohabir V, Lalloo C, Briggs AM, et al. The transformative potential of digital therapeutics in pediatrics. *PAIN*. 2025;166(11s):S121–S130. <https://doi.org/10.1097/j.pain.0000000000003713>.
18. Court RJ, Swallow V, El-Youssi S, et al. Children and young people's preferences and needs when using health technology to self-manage a long-term condition: a scoping review. *Arch Dis Child*. 2024;109(10):826–835. <https://doi.org/10.1136/archdischild-2023-326044>.
19. Gershkowitz BD, Hillert CJ, Crotty BH. Digital coaching strategies to facilitate behavioral change in type 2 diabetes: a systematic review. *J Clin Endocrinol Metab*. 2021;106(4):e1513–e1520. <https://doi.org/10.1210/clinem/dgaa850>.
20. Lattie EG, Adkins EC, Winquist N, Stiles-Shields C, Wafford QE, Graham AK. Digital mental health interventions for depression, anxiety, and enhancement of psychological well-being among college students: systematic review. *J Med Internet Res*. 2019;21(7), e12869. <https://doi.org/10.2196/12869>.
21. Ames HM, Glenton C, Lewin S, Tamrat T, Akama E, Leon N. Clients' perceptions and experiences of targeted digital communication accessible via mobile devices for reproductive, maternal, newborn, child, and adolescent health: a qualitative evidence synthesis. *Cochrane Database Syst Rev*. 2019;10(10):Cd013447. <https://doi.org/10.1002/14651858.Cd013447>.
22. World Health Organization. *Youth-centred digital health interventions: a framework for planning, developing and implementing solutions with and for young people*. WHO. Geneva: 2020. Accessed 11 December 2025. (<https://www.who.int/publications/i/item/9789240011717>).
23. Gradon KT. Generative artificial intelligence and medical disinformation. *BMJ*. 2024;384:q579. <https://doi.org/10.1136/bmj.q579>.
24. Etzioni A, Etzioni O. AI assisted ethics. *Ethics Inf Technol*. 2016;18(2):149–156. <https://doi.org/10.1007/s10676-016-9400-6>.
25. Sorich MJ, Menz BD, Hopkins AM. Quality and safety of artificial intelligence generated health information. *BMJ*. 2024;384:q596. <https://doi.org/10.1136/bmj.q596>.
26. Blower S, Swallow V, Maturana C, et al. Children and young people's concerns and needs relating to their use of health technology to self-manage long-term conditions: a scoping review. *Arch Dis Child*. 2020;105(11):1093–1104. <https://doi.org/10.1136/archdischild-2020-319103>.
27. Scott IA, van der Vegt A, Lane P, McPhail S, Magrabi F. Achieving large-scale clinician adoption of AI-enabled decision support. *BMJ Health Care Inf*. 2024;31(1), e100971. <https://doi.org/10.1136/bmjhci-2023-100971>.
28. van der Vegt A, Campbell V, Zuccon G. Why clinical artificial intelligence is (almost) non-existent in Australian hospitals and how to fix it. *Med J Aust*. 2024;220(4): 172–175. <https://doi.org/10.5694/mja2.52195>.
29. McFadden D. Conditional logit analysis of qualitative choice behavior. In: Zarembka P, ed. *Frontiers in Econometrics*. Academic Press; 1974:105–142.
30. Zhu M, Dong D, Lo HH, Wong SY, Mo PK, Sit RW. Patient preferences in the treatment of chronic musculoskeletal pain: a systematic review of discrete choice experiments. *PAIN*. 2023;164(4):675–689. <https://doi.org/10.1097/j.pain.0000000000002775>.
31. Crotty M. *The foundations of social research: meaning and perspective in the research process*. Thousand Oaks, CA: Sage; 1998.
32. von Elm E, Altman DG, Egger M, Pocock SJ, Gotsche PC, Vandenbroucke JP. The strengthening of reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. *Lancet*. 2007;370(9596): 1453–1457. [https://doi.org/10.1016/s0140-6736\(07\)61602-x](https://doi.org/10.1016/s0140-6736(07)61602-x).
33. Tovim MM, Wormley ME. Systematic development of standards for mixed methods reporting in rehabilitation health sciences research. *Phys Ther*. 2023;103(11), pzad084. <https://doi.org/10.1093/ptj/pzad084>.
34. Nagata JM, Imbago-Jácime D, Choonara S, et al. Reporting of research with adolescent and youth engagement. *Lancet Child Adolesc Health*. 2025;9(7):442–445. [https://doi.org/10.1016/S2352-4642\(25\)00092-6](https://doi.org/10.1016/S2352-4642(25)00092-6).
35. Eysenbach G. Improving the quality of Web surveys: the Checklist for Reporting Results of Internet E-Surveys (CHERRIES). *J Med Internet Res*. 2004;6(3), e34. <https://doi.org/10.2196/jmir.6.3.e34>.
36. Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. *Int J Qual Health Care*. 2007;19(6):349–357. <https://doi.org/10.1093/intqhc/mzm042>.
37. Jünger S, Payne SA, Brine J, Radbruch L, Brearley SG. Guidance on Conducting and REporting DELphi Studies (CREDES) in palliative care: recommendations based on a methodological systematic review. *Palliat Med*. 2017;31(8):684–706.
38. Ride J, Goranitis I, Meng Y, LaBond C, Lancsar E. A reporting checklist for discrete choice experiments in health: the DIRECT checklist. *Pharmacoeconomics*. 2024;42(10):1161–1175. <https://doi.org/10.1007/s40273-024-01431-6>.
39. Chua J, Slater H, Rowbotham S, et al. What informs choices young people with chronic musculoskeletal pain make about their pain care? *Disabil Rehabil*. 2025: 1–21. <https://doi.org/10.1080/09638288.2025.2585762>.
40. Potter M, Gordon S, Hamer P. The nominal group technique: a useful consensus methodology in physiotherapy research. *NZJ Physiother*. 2004;32(3):126.
41. Hsieh H-F, Shannon SE. Three approaches to qualitative content analysis. *Qual Health Res*. 2005;15(9):1277–1288. <https://doi.org/10.1177/1049732305276687>.
42. Ayton D, Tsindos T, Berkovic D. *Qualitative Research: a practical guide for health and social care researchers and practitioners*. Open textbook library. Clayton, Victoria: Monash University; 2024.
43. Hansen P, Ombler F. A new method for scoring additive multi-attribute value models using pairwise rankings of alternatives. *J Multi-Criteria Decis Anal*. 2008;15(3–4):87–107. <https://doi.org/10.1002/mcda.428>.
44. Sullivan T, Hansen P, Ombler F, Derrett S, Devlin N. A new tool for creating personal and social EQ-5D-5L value sets, including valuing 'dead. *Soc Sci Med*. 2020;246, 112707. <https://doi.org/10.1016/j.socscimed.2019.112707>.
45. Li Z, Lu F, Wu J, et al. Usability and effectiveness of eHealth and mHealth interventions that support self-management and health care transition in adolescents and young adults with chronic disease: systematic review. *J Med Internet Res*. 2024;26, e56556. <https://doi.org/10.2196/56556>.
46. Lalloo C, Harris LR, Hundert AS, et al. The iCanCope pain self-management application for adolescents with juvenile idiopathic arthritis: a pilot randomized controlled trial. *Rheumatol (Oxf)*. 2021;60(1):196–206. <https://doi.org/10.1093/rheumatology/keaa178>.
47. Palermo TM, Lalloo C, Zhou C, et al. A cognitive-behavioral digital health intervention for sickle cell disease pain in adolescents: a randomized, controlled, multicenter trial. *PAIN*. 2024;165(1):164–176. <https://doi.org/10.1097/j.pain.0000000000003009>.
48. Palermo TM, de la Vega R, Murray C, Law E, Zhou C. A digital health psychological intervention (WebMAP Mobile) for children and adolescents with chronic pain: results of a hybrid effectiveness-implementation stepped-wedge cluster randomized trial. *PAIN*. 2020;161(12):2763–2774. <https://doi.org/10.1097/j.pain.0000000000001994>.
49. Karran EL, Cashin AG, Chiarotto A, et al. Identifying Social factors that Stratify Health Opportunities and Outcomes (ISSHOOs) in pain research: consensus recommendations for the collection and reporting of equity-relevant data. *eClinicalMedicine*. 2025;90, 103586. <https://doi.org/10.1016/j.eclinm.2025.103586>.
50. Wijnhoven HA, de Vet HC, Picavet HS. Prevalence of musculoskeletal disorders is systematically higher in women than in men. *Clin J Pain*. 2006;22(8):717–724. <https://doi.org/10.1097/01.jpain.0000210912.95664.53>.
51. Phillips N, Brown BT, Hestbaek L, et al. What are the consequences of musculoskeletal pain in adolescents? A critical qualitative systematic review and meta-synthesis. *J Pain*. 2025;32, 105418. <https://doi.org/10.1016/j.jpain.2025.105418>.
52. Xie Y, Fadahansi KP, Kelleher C, Tarn DM, Grace A, O'Donoghue J. Towards an inclusive digital health ecosystem. *Bull World Health Organ*. 2024;103(2):170.
53. Kerr D, Ahn D, Waki K, Wang J, Breznen B, Klonoff DC. Digital interventions for self-management of type 2 diabetes mellitus: systematic literature review and meta-analysis. *J Med Internet Res*. 2024;26, e55757. <https://doi.org/10.2196/55757>.
54. Lazarou J, Krooupa A-M, Nikolopoulos S, et al. Cancer patients' perspectives and requirements of digital health technologies: a scoping literature review. *Cancers*. 2024;16(13):2293.
55. Lin I, Wiles L, Waller R, et al. What does best practice care for musculoskeletal pain look like? Eleven consistent recommendations from high-quality clinical practice guidelines: systematic review. *Br J Sports Med*. 2020;54(2):79–86. <https://doi.org/10.1136/bjsports-2018-099878>.
56. Partridge SR, Todd AR, Jia SS, Raeside R. Shifting focus to adolescent wellbeing and inclusive participation in the digital age. *Med J Aust*. 2025;222(10):484–487. <https://doi.org/10.5694/mja2.52653>.
57. World Health Organisation. *Principles of health benefit packages*. WHO. Geneva: 2021. Accessed 11 December 2025. (<https://www.who.int/publications/b/57180>).
58. World Health Organisation. *From value for money to value-based health services: a twenty-first century shift*: WHO policy brief. WHO. Geneva: 2021. Accessed 11 December 2025. (<https://www.who.int/publications/b/57126>).
59. Qian T, Walton AE, Collins LM, et al. The microrandomized trial for developing digital interventions: Experimental design and data analysis considerations. *Psychol Methods*. 2022;27(5):874–894. <https://doi.org/10.1037/met0000283>.
60. Murphy SA. An experimental design for the development of adaptive treatment strategies. *Stat Med*. 2005;24(10):1455–1481. <https://doi.org/10.1002/sim.2022>.
61. Lauffenburger JC, Choudhry NK, Russo M, Glynn RJ, Vantz S, Trippa L. Designing and conducting adaptive trials to evaluate interventions in health services and implementation research: practical considerations. *BMJ Med*. 2022;1(1). <https://doi.org/10.1136/bmjmed-2022-000158>.
62. Kessler RC, Barker PR, Colpe LJ, Epstein JF, Gfroerer JC, Hiripi E, et al. Screening for serious mental illness in the general population. *Arch Gen Psychiatry*. 2003 Feb;60(2):184–189.

63. Nicholas MK. The pain self-efficacy questionnaire: Taking pain into account. *Eur J Pain*. 2007;11(2):153–163. <https://doi.org/10.1016/j.ejpain.2005.12.008>. Epub 2006 Jan 30. PMID: 16446108.
64. Cleeland CS, Ryan KM. Pain assessment: global use of the Brief Pain Inventory. *Ann Acad Med Singapore*. 1994;23(2):129–138.
65. Walton DM, Mehta S, Seo W, MacDermid JC. Creation and validation of the 4-item BriefPCS-chronic through methodological triangulation. *Health Qual Life Outcomes*. 2020;18(1). <https://doi.org/10.1186/s12955-020-01346-8>. PMID: 32381020; PMCID: PMC7204020.