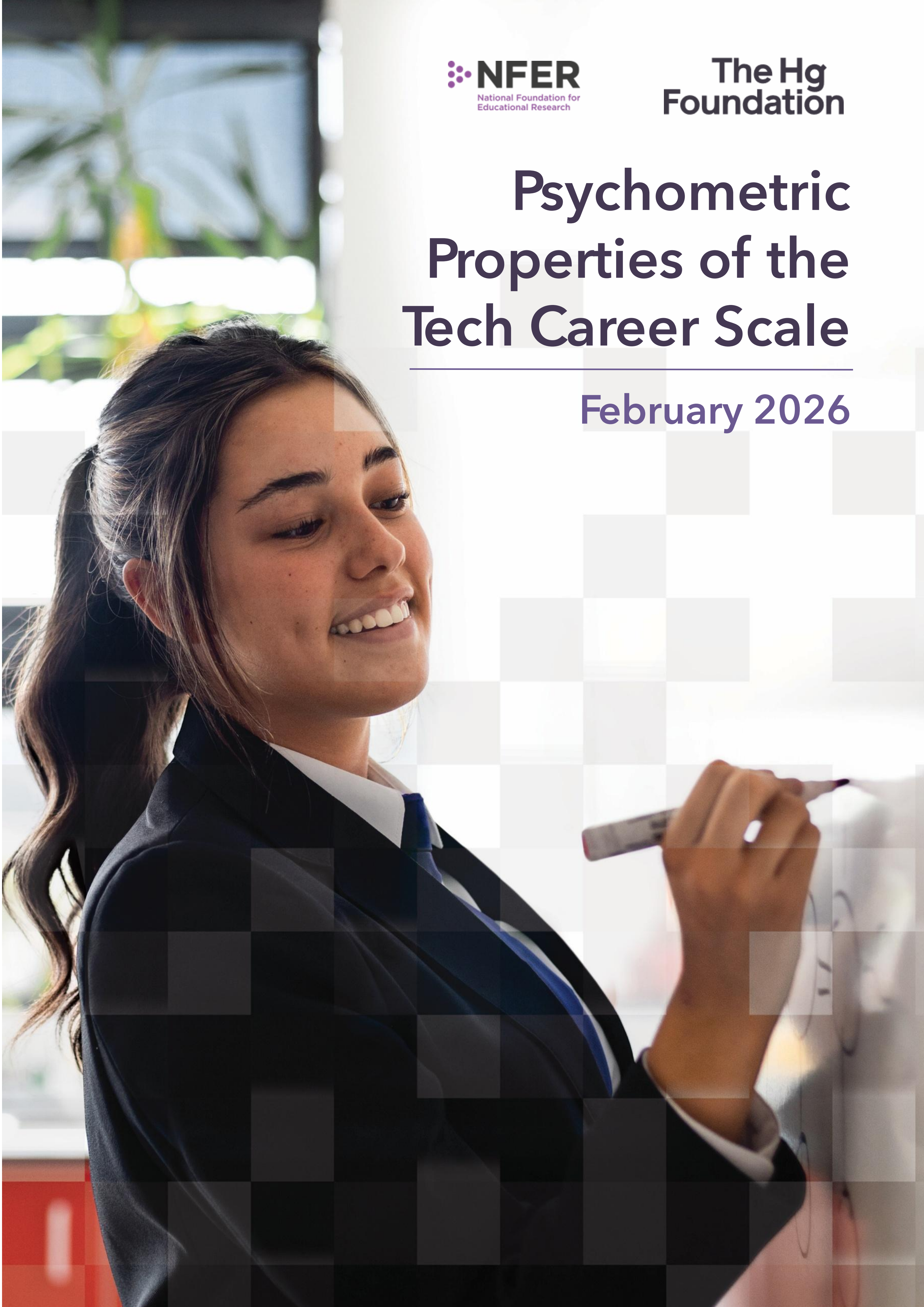

Psychometric Properties of the Tech Career Scale

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Contents

1	Executive Summary	4
1.1	Background	4
1.2	Methods	4
1.3	Results	4
1.4	Conclusion	5
2	Background	6
3	Method	6
3.1	Scale Development	6
3.2	Additional Measures	7
3.3	Design	7
3.4	Sample and Recruitment	7
4	Results	8
4.1	Phase 1: Exploratory Factor Analysis	8
4.2	Phase 2: Confirmatory Factor Analysis of the Tech Career Scale	19
4.3	Scoring	26
5	Conclusion	28

Appendix A: Development and Validation of the Career Knowledge Scale and Personal Skills Scale. 29

Appendix B: Descriptive statistics 38

Appendix C: Tech Career Scale final version 42

References 46

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1 Executive Summary

1.1 Background

Understanding student's knowledge and attitudes towards particular careers, as well as the behaviours that they engage in towards those careers, is important to determine career support or training needs, and also to better understand the careers landscape of young people. While scales to measure general careers knowledge exist, there is a paucity of validated scales specifically measuring tech careers knowledge, attitudes and behaviours. The Hg Foundation therefore commissioned NFER to develop the Tech Career Scale – a self-report measure of knowledge, attitudes, and behaviours towards careers in tech for adolescents. The first use of this scale is intended to be in The Hg Foundation co-funded evaluation of Futures For All's IntoTech Programme, which is designed to improve children's knowledge of and attitudes towards careers in tech.

1.2 Methods

The Tech Career Scale was developed with participating students from Year 10 classes in schools in England. The study had two phases. The aim of the first phase was to develop an initial pool of items and explore their factor structure using exploratory factor analysis. Collaboratively, NFER, The Hg Foundation and Futures For All, proposed the Tech Career Scale to have three subscales: Knowledge, Attitudes and Behaviours. Guided by this three-subscale structure, 43 items were trialled in the first phase. Data from 474 pupils from 14 schools were analysed in the first phase, and the results of this analysis were used to refine and revise items in the Tech Career Scale. The aim of the second phase was to confirm the structure of the Tech Career Scale using confirmatory factor analysis in an independent sample. Data from 2,011 pupils across 29 schools were analysed in the second phase.

In order to validate the Tech Career Scale, an additional validation scale measuring students' intended A Level choices was developed and administered alongside the Tech Career Scale in phases 1 and 2. This additional scale comprised three items asking students how likely they were to study a i) Maths, ii) Science, or iii) technology-based subject. The idea being that if the tech scale measures important aspects of young people's attitudes, knowledge and behaviours towards tech we should also expect to see correlations with anticipated A Level choices compatible with an eventual career in tech.

It is also worth noting that two additional scales, measuring General Career Knowledge and Personal Skills, were also developed, in parallel with the Tech Career Scale, for the purpose of the IntoTech Programme evaluation. These additional scales were administered to the same group of students and are reported in the appendices of this report.

1.3 Results

In the first phase of the study an exploratory factor analysis was performed on the data. The results of the exploratory factor analysis indicated a four-factor structure, in contrast to the hypothesised three factors, with the fourth factor aligning with perceived barriers to a career in Tech. The analysis also informed several minor item changes in the Tech Career Scale: one item was removed, one item was rewritten, and several items were reworded to improve clarity.

Following item changes, in the second phase of the study, the four-factor structure of the Tech Careers Scale was analysed in an independent sample using confirmatory factor analysis. The results of the confirmatory analysis suggested that the four-factor model was an acceptable fit to the data, supporting the four-subscale structure of the Tech Careers Scale (Knowledge, Attitudes, Behaviours, Barriers). Fit indices were close to, or within range, and standardized factor loadings were moderate-strong on all subscales. The Knowledge, Attitudes, and Behaviours subscales all correlated positively with one another with moderate strength. However, the Barriers subscale correlated negatively with the other three subscales, suggesting that it does not align with them. Correlations between the four subscales and the additional validation scale (measuring student's A Level choices) were sufficient for three out of the four subscales: Knowledge, Attitudes, and Behaviours had correlations of greater than 0.3, however Barriers had a correlation near zero suggesting this subscale is not a good predictor of tech-related A Level choices. Reliability estimates of the final scale and subscales were acceptable to excellent; Knowledge ($\alpha = 0.92$), Attitudes ($\alpha = 0.86$), Behaviours ($\alpha = 0.94$), Barriers ($\alpha = 0.69$), and overall Tech Career Scale ($\alpha = 0.94$), supporting the internal consistency of the scales. The median time to compete the Tech Career scale was 8 minutes 5 seconds with an interquartile range (IRQ) of 4 minutes 28 seconds.

1.4 Conclusion

This study reports the development and validation of the Tech Career Scale, a 42-item self-report instrument measuring Knowledge (12 items), Attitudes (10 items), Behaviours (14 items) and Barriers (6 items) towards careers in tech. It was developed for use with secondary school-aged children (typically those aged 11 – 18 in England). The final scale is made up of a mix of seven-point ordered Likert items and Yes/No items. Factor analyses of the Tech Career Scale supported a coherent four-factor structure, as well as acceptable-to-excellent reliability estimates on individual subscales and for the overall scale. The Tech Career Scale could have a range of different uses, including for programmes to measure the knowledge, attitudes and behaviours towards a career in tech of their participants, or for use in independent impact evaluations. We recommend that the Barriers subscale can be treated as an optional additional subscale and that the overall Tech measure should only include items from the other three scales. The Barriers subscale remains a psychometrically robust independent scale to measure perceived barriers into tech careers, the results of which can complement a calculated overall Tech Career Scale score.

2 Background

The Hg Foundation is interested in supporting its partners to measure impact on outcomes they target through their programmes. It commissioned NFER to develop a measure of knowledge, attitudes and behaviours regarding tech careers, including relevant education pathways, that could be validated against actual STEM and tech-related education (e.g. A Level) choices. The first version of the measure was developed and piloted as part of the Futures For All IntoTech Programme evaluation (looking at the impact of providing inspirational talks, insight days and work experience on intentions and outcomes for FSM pupils).

While there exist several scales to measure career knowledge more generally, for example the Future Skills Questionnaire (Tanner and Finlay, 2021), there is a paucity of validated scales comprehensively measuring attitudes towards, and interest in, pursuing *tech* careers. The current research reports the development and psychometric validation of the Tech Career Scale, a 42-item self-report instrument measuring knowledge, attitudes, behaviours and barriers towards careers in tech.

The Tech Career Scale was developed to be suitable for secondary aged children and was tested on children aged 14-15 years (UK Year 10). The scale has four subscales:

i) *Knowledge* (12 items) – measuring actual and perceived knowledge about tech careers and tech skills/education,

ii) *Attitudes* (10 items) – measuring perceptions of the appeal, accessibility, and value of tech careers,

iii) *Behaviours* (14 items) – measuring interest in, or intention to pursue, a tech career or tech skills/education and

iv) *Barriers* (6 items) – measuring perceived barriers to pursuing a career in tech.

'*Careers in tech'* is defined at the start of the survey using example careers of "data analytics, programming and working with code, cyber security, artificial intelligence (AI), digital marketing, gaming, technology research, software development, and IT support".

3 Method

3.1 Scale Development

Initially, 82 items were written for what was envisaged to be a 3-factor scale: Knowledge (29 items), Attitudes (23 items) and Behaviours (30 items). These items were written by NFER test developers using definitions of the constructs (*knowledge*, *attitudes*, and *behaviours* towards tech careers) that had been collaboratively created between NFER, The Hg Foundation and Future For All (formerly Speakers for Schools). Following these consultations, 43 of these items were retained for the first phase of the study (13 Knowledge, 16 Attitudes, and 14 Behaviours items). Retained items were evaluated to have high construct relevance, age appropriateness, and clarity. 34 of the items were measured on a seven-point ordered Likert scale of agreement, from (1) *Strongly Disagree* to (7) *Strongly Agree*, with a neutral mid-point of (4) *Neither Agree nor Disagree.* Nine of the items on the behaviours subscale, which related to past behaviours, were measured on a binary scale (Yes/No). Seven items on the scale were negatively keyed (two Knowledge and five Attitudes items).

3.2 Additional Measures

To test the convergent validity of the Tech Career Scale three additional items were written and included in Phases 1 and 2 of the research. These items asked how likely it was that students would study i) a Maths subject(s) (e.g., Maths, Statistics), ii) a Science subject(s) (e.g., Biology, Chemistry, Physics), and iii) a Technology subject (e.g., Software Engineering, Computer Science, Design and Technology) in the future. For the purposes of validation these items were treated as a separate scale with the correlation between these three items and each subscale of the outcome measure used to gauge the validity of the measure. Two additional measures relating to careers knowledge and personal skills were piloted and are outlined in Appendix A.

3.3 Design

To develop and validate the Tech Career Scale a two-phase study design was employed. The first phase aimed to explore the structure of the Tech Career Scale, and the second phase aimed to confirm this structure in an independent sample.

3.4 Sample and Recruitment

Two school samples were selected for the outcome measure piloting, as identified in Table 1. below. These samples were drawn from the list of secondary maintained schools in England, where there were at least 30 (for Phase 1) or 60 (for Phase 2) students in Year 10 that the school was willing to administer the measure to. Schools were contacted via email, to encourage their participation. Schools could take part in either one, or both phases, but schools were instructed that no pupil who had undertaken the survey in Phase 1 could take it again in Phase 2.

Table 1: Target sample

Sample	School type	Year group	No. of schools in sample	Target No. of schools	Target No. of pupils
Phase 1	Secondary, maintained	10	1600	16	480 30 per school
Phase 2 additional sample	Secondary, maintained	10	3190	34	2040 60 per school

3.4.1 Phase 1

An initial 800 schools were contacted. Responses were slow, and a top-up of a further 800 schools was requested. Following the initial email, 7 further reminders were sent to achieve the 16 schools needed for Phase 1.

3.4.2 Phase 2

Phase 2 recruitment overlapped with the live survey for Phase 1, with all previous schools (apart from 6 who had declined) re-invited to participate with different pupils and a further sample of 1596 secondary schools added to this for Phase 2. Following the initial Phase 2 recruitment emails, 4 reminders were sent. Ultimately 36 schools were recruited for Phase 2. The response achieved for both phases is outlined in Table 2.

Table 2: Achieved response

Stage	No. of schools	
	Phase 1	Phase 2
Drawn in sample	1600	3190
Withdrawn by LA	0	0
Invited to participate	1600	3190
School closed	0	0
Declined at invitation stage	6	2
No response	1578	3152
Agreed to participate	16	36
Withdrew after dispatch	2	7
Schools returning completed tests/questionnaires (Number of completed questionnaires)	14 (474)	29 (2011)

In total, 474 pupils from 14 schools provided valid responses in Phase 1, and their data was used for the exploratory factor analysis (EFA). In Phase 2, 2,181 pupils across 29 schools submitted responses, of which 2,011 were fully complete and were included in the confirmatory factor analysis (CFA). No pupils participated in both phases, and only one survey submission per pupil was permitted. The median time to complete the survey was 8 minutes 5 seconds, with an interquartile range of 4 minutes 28 seconds, which means that 75% of participants completed the survey within 12 minutes 33 seconds.

It should be noted that this was a convenience rather than a representative sample of schools but looking at the mean percentage of FSM (Phase 1 = 27.0%, Phase 2 = 24.7%) and girls (Phase 1 = 52.0%, Phase 2 = 52.0%) they are similar to the national average.

4 Results

4.1 Phase 1: Exploratory Factor Analysis

4.1.1 Data Preparation

Prior to Exploratory Factor Analysis, item polarity was harmonised so that higher scores consistently indicated a higher score on the underlying construct. Negatively keyed Likert items were reversed and binary items were aligned so that the affirmative response indexed higher scores on the latent trait. This pre-processing reduces spurious negative associations and clarifies interpretation of factor loadings and communalities in subsequent stages (Fabrigar *et al.*, 1999; Yong and Pearce, 2013). The factorability of each scale was evaluated using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. KMO assesses the proportion of common variance relative to partialled variance; values around .60 are commonly considered a lower bound for proceeding, with .70–.80 indicative of good to very good adequacy (Kaiser, 1974; Yong and Pearce, 2013). Bartlett's test examines whether the correlation matrix departs from identity, supporting the presence of sufficient shared variance for extraction (Bartlett, 1950). These diagnostics were treated as necessary but not sufficient conditions: they justify moving to factor extraction and help identify items requiring closer scrutiny.

For the scale, KMO measure of sampling adequacy was .91, which indicates very substantial common variance suitable for factor analysis (Kaiser, 1974). Bartlett's test of sphericity was significant, (903) = 10,892.20, $p < .001$, rejecting the null hypothesis that the correlation matrix is an identity matrix and confirming that the items share enough variance for factoring (Bartlett, 1950). Internal consistency for the item set was *alpha*= 0. 918, suggesting high reliability (Sijtsma, 2009). Taken together, these indices provide strong empirical justification for the exploratory factor analyses reported below.

4.1.2 Estimation and Factor Extraction

The item pool comprised a mixture of seven-point ordered Likert items and binary Yes/No indicators. Analysing such responses with Pearson correlations implicitly treats categories as equally spaced and continuous, an assumption that is often untenable for ordinal variables and can attenuate or distort the associations that drive factor extraction (Flora and Curran, 2004; Rhemtulla, Brosseau-Liard and Savalei, 2012). To align the measurement model with the response process, a polychoric correlation matrix was estimated and all exploratory factor analyses (EFA) were fitted to that matrix rather than to raw scores. Under the latent-response framework, each ordinal response reflects thresholds on an underlying continuous propensity; polychoric correlations estimate the association between these latent propensities (Olsson, 1979; Holgado–Tello *et al.*, 2010). Methodological studies show that factor solutions based on polychoric (rather than Pearson) correlations more accurately recover the intended structure for ordinal indicators (Flora and Curran, 2004; Holgado–Tello *et al.*, 2010).

Factors were extracted using principal axis factoring (PAF) applied to the polychoric matrix. PAF targets common variance and is comparatively robust to violations of multivariate normality that are typical of ordinal data (Fabrigar *et al.*, 1999; Costello and Osborne, 2005). For descriptive comparison and to aid visual assessment of dimensionality, a principal components analysis (PCA) was also run on the same polychoric matrix; PCA results were used for variance summaries and scree inspection, not for interpreting latent constructs because components combine common and unique variance and therefore do not constitute a measurement model (Fabrigar *et al.*, 1999).

The number of factors retained for each instrument was guided by theory and empirical diagnostics. The scree plot of polychoric eigenvalues was inspected for elbows that separate substantive factors from minor ones (Cattell, 1966) the proportion of common variance explained was considered, and interpretability was judged in terms of simple structure. Interpretation rules were applied consistently while preserving content coverage. Primary factor loadings of .30 or above were deemed sufficient (Field, 2024).

4.1.3 Analysis

Factor loadings, item level KMO, communalities, factor correlations, variance accounted for, and a PCA variance summary with a scree plot based on polychoric eigenvalues, were calculated in the analysis. Through evaluation of the factor loadings (Table 3) and scree plot (Figure 1), it was determined that a four-factor solution was the best fit for the data. Variance summaries of the factor analysis are reported in Tables 4 and 5. These four factors reflected the three anticipated *Knowledge*, *Attitudes*, and *Behaviours* subscales, as well as an unexpected fourth subscale, comprised of five items. The items in the fourth subscale were assessed to reflect perceived barriers to tech careers (e.g., "*To get a tech job, you need to know someone in the industry*"), and this subscale was therefore labelled '*Barriers*'.

Table 3: Factor Loadings

		Factor 1 (Behaviours)	Factor 2 (Knowledge)	Factor 3 (Attitudes)	Factor 4 (Barriers)	KMO	Communality
A1	*"I can think of several different tech jobs."*	0.10	0.51	0.26	0.03	0.92	0.46
A2	*"I know what sort of tasks people might do in different tech jobs."*	0.05	0.59	0.22	0.04	0.91	0.51
A3	*"I know about different types of companies that employ people to do tech jobs."*	-0.02	0.60	0.16	-0.02	0.95	0.43
A4	*"I have enough information about tech careers to make decisions about whether I want to go into a tech career."*	-0.01	0.74	-0.04	0.06	0.95	0.53
A5	*"I know roughly how much you get paid in different tech jobs."*	0.03	0.74	-0.12	-0.01	0.93	0.53
A6	*"I know about which tech jobs are likely to provide opportunities for promotion."*	0.02	0.72	-0.12	-0.09	0.90	0.50

A7	*"I don't know much about tech careers."*	0.24	0.44	-0.23	0.26	0.88	0.36
B1	*"I know about courses I could take at school/college after Year 11 that could help me to get a career in tech (e.g., A-levels, T Levels, BTECs)."*	-0.06	0.62	0.15	0.03	0.92	0.43
B2	*"I am aware of the different apprenticeship options for a career in tech."*	0.02	0.72	-0.01	-0.03	0.91	0.53
B3	*"I know what sort of degree courses I could study at university to help me to have a career in tech."*	-0.05	0.77	0.05	0.00	0.93	0.58
B4	*"I do not have enough information about qualifications that would help me to get into a tech career."*	0.15	0.09	-0.25	0.30	0.63	0.14
B5	*"I understand the skills that would be useful for a career in tech."*	0.09	0.59	0.23	-0.01	0.95	0.53
B6	*"I know about the different ways to get into a tech career."*	-0.06	0.83	0.00	-0.05	0.94	0.65

C1	*"Only the cleverest people can enter tech jobs."*	0.05	0.01	-0.03	0.71	0.62	0.50
C2	*"To get a tech job, you need to know someone in the industry."*	-0.04	-0.07	0.16	0.58	0.67	0.39
C3	*"People who work in tech can make a positive difference in the world."*	0.13	0.09	0.61	-0.03	0.92	0.47
C4	*"You don't need to go to university to have a good career in tech."*	0.04	0.24	0.19	0.07	0.92	0.14
C5	*"A tech career would mean working with interesting people."*	0.11	0.13	0.49	-0.10	0.90	0.34
C6	*"Women can do well in tech careers."*	-0.18	-0.05	0.60	0.26	0.79	0.44
C7	*"Tech careers are difficult to get in to."*	-0.04	0.07	-0.28	0.46	0.66	0.27
C8	*"A person's background would not stop them from having a tech career."*	0.02	0.05	0.43	-0.05	0.84	0.20
C9	*"Tech jobs can create solutions to important*	0.15	0.08	0.64	-0.04	0.88	0.52

	challenges we face."						
C10	*"A tech job would involve doing interesting work."*	0.25	0.09	0.59	-0.08	0.91	0.54
C11	*"Tech careers are better suited to men."*	-0.16	-0.16	0.25	0.48	0.70	0.36
C12	*"There are people from all different cultural backgrounds in the tech industry."*	0.02	0.01	0.69	0.13	0.85	0.52
C13	*"Tech jobs are boring."*	0.53	-0.01	0.05	0.23	0.91	0.34
C14	*"People who work in tech are respected by others."*	-0.02	0.19	0.46	-0.12	0.92	0.29
C15	*"I feel confident I could have a career in tech if I wanted to."*	0.42	0.35	0.10	0.08	0.95	0.47
C16	*"Tech careers are an option for most people, if they want it."*	0.02	0.24	0.40	0.09	0.89	0.29
D1	*"I think I would be well-suited to a career in tech."*	0.79	0.05	0.02	0.01	0.94	0.66
D2	*"I plan to look for information about tech careers."*	0.86	0.01	0.05	-0.01	0.94	0.77
D3	*"I am interested in taking tech-related*	0.78	0.01	0.10	0.02	0.95	0.66

	subjects/courses (e.g., maths, science, computer science, design and technology) and/or doing a tech-related apprenticeship.”						
D4	*“I would like to do tech-related work experience.”*	0.92	-0.07	0.03	-0.02	0.93	0.81
D5	*“In the future, I would consider doing a tech-related degree.”*	0.90	-0.04	0.03	-0.02	0.93	0.79
D6	*“In the future, I want to apply for jobs in the tech industry.”*	0.92	-0.04	0.01	-0.09	0.94	0.83
E1	*“I have searched online for education or training that would help me get a career in tech.”*	0.52	0.10	-0.15	0.00	0.92	0.31
E2	*“I am/have been a member of a computing/coding/ STEM club in or outside of school (STEM: Science, Technology, Engineering, and Maths).”*	0.32	0.14	-0.14	0.04	0.88	0.15
E3	*“I have told my friends/family/carers/teachers that I want to have a career in tech.”*	0.64	0.02	-0.06	0.02	0.94	0.41

E4	*“My hobbies and interests are related to tech.”*	0.51	0.05	-0.08	0.15	0.94	0.28
E5	*“I have asked for careers advice about how to get into a tech career.”*	0.51	0.04	-0.15	0.00	0.90	0.26
E6	*“I have searched tech jobs online.”*	0.50	0.12	-0.10	0.14	0.93	0.31
E7	*“I have learnt some tech skills outside of school e.g., coding.”*	0.38	0.15	-0.04	0.06	0.90	0.20
E8	*“I know someone who works in tech.”*	0.03	0.14	0.09	0.10	0.77	0.05

Note. Items A1:D6 were scored on a 7-point Likert scale of agreement, and items E1:E8 were scored on a binary Yes/No scale. Columns Factor 1-Factor 4 report the factor loadings of each individual factor. Factor loadings greater than 0.3 – the threshold for acceptable factor loadings – are shown in bold font.

Figure 1: Scree plot of the Tech Career Scale.

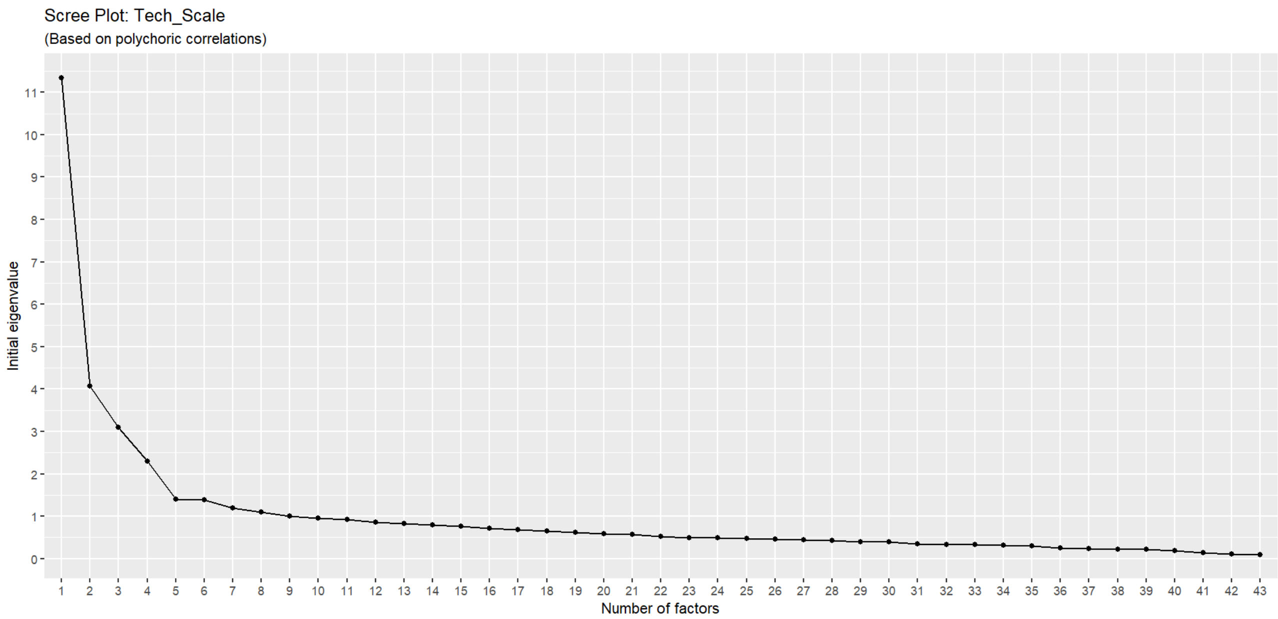


Table 4 reports the initial eigenvalues from the correlation matrix. Component 1 has an eigenvalue of 11.35 and explains 26.39% of the total variance; Components 2 and 3 add 9.46% and 7.21%, respectively, for a cumulative 43.06% after three components. The eigenvalue profile showed a clear elbow after the third component (26.39%, 9.46%, 7.21%; cumulative 43.06%), with subsequent components contributing < 2% each by the 15th (eigenvalue = .76), suggesting a 4-factor solution for follow-up CFA.

Table 4: Variance Summary

Component	Eigenvalue	% of Variance	Cumulative %
1	11.346	26.39	26.39
2	4.069	9.46	35.85
3	3.099	7.21	43.06
4	2.292	5.33	48.39
5	1.395	3.24	51.63
6	1.377	3.20	54.83
7	1.189	2.77	57.60
8	1.097	2.55	60.15
9	0.996	2.32	62.47
10	0.951	2.21	64.68
11	0.920	2.14	66.82
12	0.866	2.01	68.83
13	0.826	1.92	70.75
14	0.800	1.86	72.61
15	0.758	1.76	74.38

Note. % of Variance = percentage of variance explained by each factor. Cumulative % = cumulative percentage of variance explained.

In Table 5, the SS loadings index each factor's captured common variance (i.e., rotated eigenvalues), while Proportion Variance expresses each factor's absolute share of total standardized item variance (SS/p), and Cumulative Variance accumulates those shares across factors; by contrast, Proportion Explained rescales contributions within the retained solution (SS/ΣSS) to show relative importance among factors, and Cumulative Proportion accumulates those relative shares (Kline, 2016). Substantively, four-factor EFA showed that Behaviours and Knowledge account for the largest portions of variance (.17 and .14 of total; .38 and .33 of model-explained), with Attitudes moderate (.09; .20) and Barriers small (.04; .09), indicating a comparatively weak and distinct Barriers dimension. Thus, balancing interpretable structures alongside quantitative fit, a four-factor model comprising Behaviours, Knowledge, Attitudes, and Barriers was retained and interpreted (Fabrigar *et al.*, 1999; Brown, 2015; Kline, 2016).

Table 5: Total Variance Explained

Metric	Factor 1 (Behaviours)	Factor 2 (Knowledge)	Factor 3 (Attitudes)	Factor 4 (Barriers)
SS loadings	7.17	6.17	3.66	1.72
Proportion Variance	0.17	0.14	0.09	0.04
Cumulative Variance	0.17	0.31	0.40	0.44
Proportion Explained	0.38	0.33	0.20	0.09
Cumulative Proportion	0.38	0.71	0.91	1.00

Note. SS loadings = sum of squared loadings of each factor.

4.1.4 Reliability

Internal consistency was estimated for each sub-dimension using Cronbach's alpha computed on the polychoric correlation matrix (ordinal alpha) and McDonald's omega (ω). Ordinal alpha is preferred for ordered-categorical items, whereas ω reflects the strength of the common factor. Two-decimal precision with 95% confidence intervals is reported where available. Table 6 reports reliability estimates for each subscale of the Tech Career Scale. Reliability estimates were above the widely used threshold of 0.8 (e.g., Nunnally, 1978) for Knowledge, Attitudes, Behaviour. The slightly lower reliability estimates for the Barriers indicates that it has less internal consistency than the other scales, possibly indicating that different children perceive different barriers. This is one reason why we suggest that this scale should be treated as an optional extra and is not included in the overall tech scale.

Table 6: Subscale Reliability (Tech Careers Scale; Polychoric-Based Estimates)

Subscale (PA)	Items (k)	Cronbach's α (ordinal)	ω (McDonald)	Mean inter-item *r* (polychoric)
Behaviours	15	0.917	0.922	0.425
Knowledge	12	0.912	0.913	0.464
Attitudes	9	0.833	0.836	0.357
Barriers	4	0.645	0.662	0.312

Note. Mean inter-item r represents the average polychoric correlation among items within each subscale, reflecting the overall strength of association between item responses.

4.1.5 Validity

Construct validity was evaluated via (a) internal structure (EFA results reported above), and (b) convergent evidence from correlations between each subscale and a validation scale constructed from the three items asking how likely it was that students would study i) Maths, ii) Science or iii) Technology subjects in the future (see Table 7.). Note that in this case it was not possible to validate the scale against another similar instrument because, as far as we are aware, this is the first scale of its kind. It is, however, reassuring that 3 of the 4 subscales correlated quite strongly ($r > 0.35$) with a preference for further study in technology-related subjects. Only the 4th (barriers) component of the scale did not correlate with this validation measure. We have elected to keep it in the scale as the overall fit was good for the four-factor model. However, we suggest that when calculating a single overall tech scale these items be omitted.

Table 7: Convergent Validity: Polychoric Correlations with Validation Scale

Tech Subscale	Validation Scale
Behaviours	0.524
Knowledge	0.361
Attitudes	0.356
Barriers	0.06
Overall	0.471

4.1.6 Item and Scale Alterations

Based on the results of the exploratory factor analysis, several minor item-level refinements were enacted on substantive grounds that had emerged during scale review:

- **Item C4**, which was not loading well onto any factor, was reworded to be positively keyed and was re-allocated from Attitudes to Barriers after re-consideration of its construct alignment.
- **Item C13** was loading onto the Behaviours subscale instead of the intended Attitudes subscale, but as the item's content did not align with the intended Behaviours construct, it was removed.
- **Item E8** did not load onto any factor and so was removed and replaced with a new item which was written to be a more specific version of the original E8 – "*I have talked to someone who works in tech about their career*".
- **Item C15** was not loading well onto the intended Attitudes subscale but *was* loading onto both the Behaviours and Knowledge subscales: This item was therefore reworded to improve clarity.
- **Items C8, 16 and 16:** Minor wording changes were made to improve clarity on three items that had lower factor loadings.

Note for items C13 and E8 the final decision was made after Phase 2 data had confirmed the pattern initially seen in Phase 1. These decisions preserved a clearly interpretable factor structure and avoided post-hoc model modifications that lacked theoretical justification (MacCallum, Roznowski and Necowitz, 1992; Marsh, Hau and Wen, 2004). Table B1 in Appendix C reports the final version of the scale. All items that were analysed in the confirmatory factor analyses of Phase 2 had appeared in the exploratory factor analyses of Phase 1.

4.2 Phase 2: Confirmatory Factor Analysis of the Tech Career Scale

4.2.1 Data Preparation

The second phase was undertaken to test the four-factor structure of the Tech Career Scale that was revealed in the Phase 1 exploratory factor analysis and content review. An independent sample was used at this stage to avoid capitalising on chance associations from the development phase and to provide an unbiased test of the hypothesised latent structure (Brown, 2015; Kline, 2016). After listwise deletion under categorical estimation, N = 2,011 of 2,181 cases contributed to the full Tech Career Scale model. In parallel with the pilot testing, the draft survey was circulated by The Hg Foundation to several partner organisations who may require a similar outcome measure in future, allowing their feedback to be incorporated into the final iteration of the instrument before Phase 2 survey administration.

4.2.2 Model and Estimator

Exploratory factor analysis had indicated a four-factor solution consistent with the intended construct map. Guided by those findings and a subsequent conceptual review, confirmatory factor analysis models were specified for a correlated-factors structure in which Attitudes, Knowledge, Behaviours, and Barriers were represented by distinct, but related, latent variables. All indicators were treated as ordered categorical variables with a limited number of response categories. This measurement level implies non-normal item distributions and discrete thresholds between categories, making estimators based on polychoric correlations preferable to maximum likelihood with continuous-normal assumptions (Flora and Curran, 2004; Rhemtulla, Brosseau-Liard and Savalei, 2012). As a formal check, multivariate normality was evaluated using Mardia’s skewness and kurtosis tests applied to each subscale and to the full item set. Results provided clear evidence against multivariate normality, with significant departures on at least one of the two Mardia components in each analysis. In line with best practice for ordinal indicators and non-normal data, robust limited-information estimators were therefore used (Li, 2016).

4.2.3 Reporting and Interpretation

Global fit indices are reported, with their confidence intervals where applicable. Standardised factor loadings with robust standard errors and z-values are tabulated by factor. For each confirmatory factor analysis, robust fit evaluation, and scrutiny of standardised loadings were used to judge whether items formed a coherent latent variable consistent with the construct definition.

4.2.4 Results: Four-factor CFA

Before examining the latent structure through confirmatory factor analysis, descriptive analyses were conducted to summarise the observed raw score characteristics of each subscale and the overall composite.

The four subscales—Attitudes, Knowledge, Behaviours, and Barriers—together with the overall composite score, demonstrated appropriate score dispersion and approximate normality, with no evidence of pronounced floor or ceiling effects (see Table B2, Appendix 2 for details).

The **Knowledge** (M = 47.07, SD = 13.7) and **Attitudes** (M = 46.63, SD = 9.7) subscales exhibited smooth, unimodal, and near-symmetric distributions centred around their midpoints, indicating balanced endorsement patterns and good coverage across the latent continua.

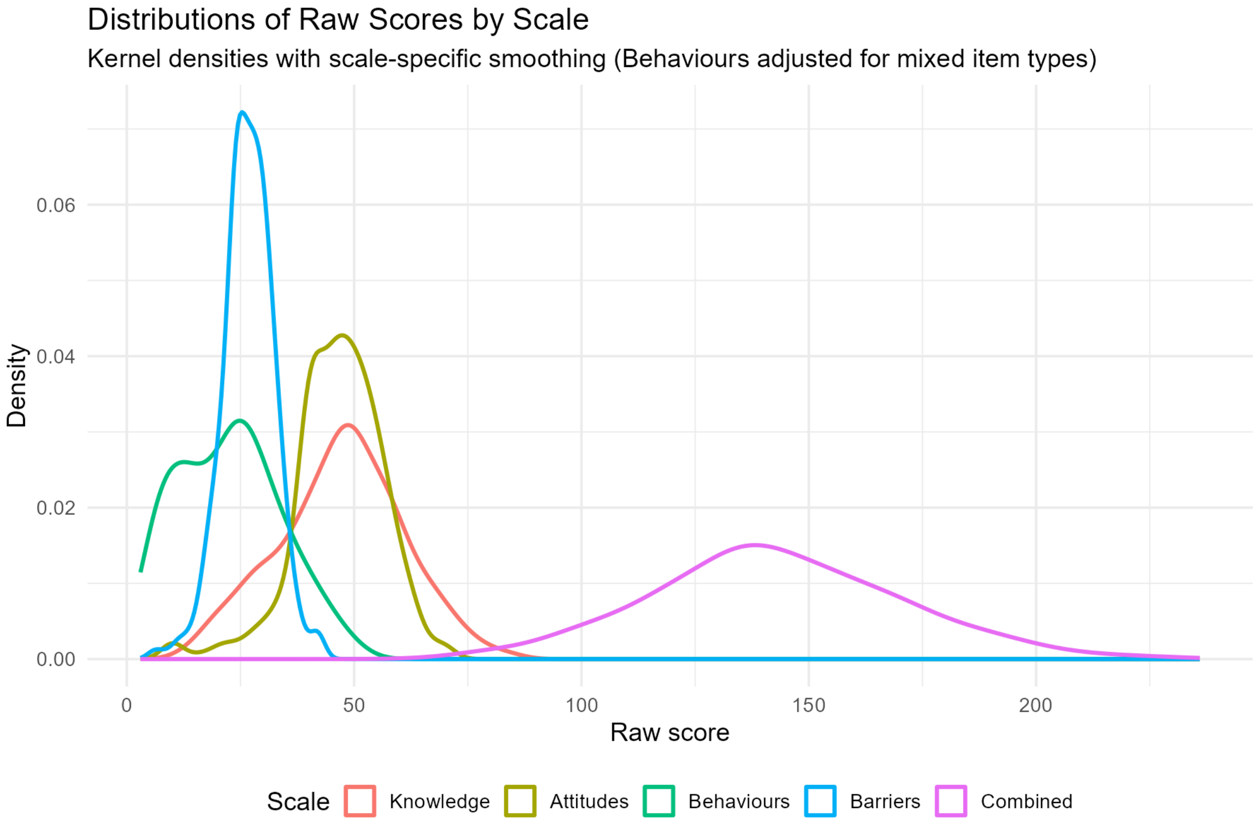
The **Barriers** subscale (M = 26.72, SD = 5.5) showed a similarly symmetric distribution, suggesting consistent variability in perceived obstacles among respondents.

The **Behaviours** subscale (M = 22.46, SD = 11.1) demonstrated a broadly unimodal distribution that was only mildly left-skewed, reflecting a concentration of scores around the mid-range. Despite the mixed item format (six Likert-type and eight dichotomous items), the overall pattern approximated a normal distribution, indicating sufficient variability without substantial ceiling or floor effects.

Finally, the **overall composite score** (M = 142.8, SD = 27.7) displayed a smooth bell-shaped curve consistent with normality, supporting the use of parametric techniques such as regression and confirmatory factor analysis, and suggesting that the combined scale captured a wide but balanced range of respondent performance levels.

Figure 2. below illustrates the combined score distributions for the four subscales and the overall composite, showing generally bell-shaped curves with only minor skew for Behaviours.

Figure 2: Distributions of raw scores



For the four-factor model (Attitudes, Knowledge, Behaviours, Barriers), the model yielded $\chi^2(861) = 41467.77$ (scaled), CFI = .793, TLI = .781, RMSEA = .072 (90% CI [.071, .074]), and SRMR = .093. In large, complex ordinal models, fit indices are known to respond differently to distributional and design features; therefore, indices were interpreted jointly rather than by single cutoffs (Hu and Bentler, 1999; Marsh, Hau and Wen, 2004; Bentler, 2007). The robust chi-square was statistically significant, as expected with a large sample size, and therefore not treated as the sole indicator of model fit (Kline, 2016). The robust CFI and TLI were below the conventional .90 benchmark, but values in this range have been judged as tolerable in complex models with many indicators (Marsh, Hau and Wen, 2004). The RMSEA indicated a moderate fit, and the SRMR indicated an acceptable level of absolute fit; (Hu and Bentler, 1999), suggesting that the model reproduced the observed correlations reasonably well. Taken together, these indices suggest that the four-factor model provides an overall adequate representation of the data.

Latent correlations were moderate (Attitudes–Knowledge r = .620; Attitudes–Behaviours r = .530; Attitudes–Barriers r = -.207; Knowledge–Behaviours r = .541), Knowledge–Barriers r = -.131; Behaviours–Barriers r = -.168

Table 8 shows that in the CFA, the Barriers factor was negatively correlated with the three substantive dimensions: Attitudes ($r = -.16$, $p < .001$), Knowledge ($r = -.18$, $p < .001$), and Behaviours ($r = -.26$, $p < .001$). These associations, although modest in size, were statistically significant, and indicate that greater perceived barriers are linked with lower levels of positive attitudes, knowledge, and behaviours, potentially suggesting Barriers is a related but distinct subdomain (Brown, 2015). In contrast, the substantive dimensions were moderately positively intercorrelated (rs = .52–.65, all ps < .001). Taken together, these findings indicate that Barriers represents a distinct construct that captures hindering perceptions, complementing the more facilitative dimensions of Attitudes, Knowledge, and Behaviours. Scoring of the Tech Career Scale is further outlined in Appendix C.

Table 8: Interfactor correlations (four-factor model)

	Attitudes	Knowledge	Behaviours	Barriers
Attitudes	1.000	0.620	0.530	-0.207
Knowledge	0.620	1.000	0.541	-0.131
Behaviours	0.530	0.541	1.000	-0.168
Barriers	-0.207	-0.131	-0.168	1.000

Note. Correlations are produced in CFA model using ULSMV estimator. Standardized loadings (latent-response metric) were substantial on all four factors (see Table 9).

- Attitudes: loadings ranged .35–.86, with the strongest relations for item C15($\lambda = .86$) and item C10 ($\lambda = .80$).
- Knowledge: loadings ranged .45–.81, with higher coefficients for item B5 ($\lambda = .81$), item B6 ($\lambda = .75$), and item B3 ($\lambda = .74$).
- Behaviours: loadings ranged .45–.87, with consistently strong coefficients for the *'D'* items (e.g., items D1, D2, D4, D5, and D6 $\lambda = .87$) and moderate-strong coefficients for the binary-scored '*E*' items (e.g., item E2 $\lambda = .45$; item E8 $\lambda = .51$; item; E3 $\lambda = .79$).
- Barriers: loadings ranged .22–.77, with mostly moderate coefficients (e.g., item C1 $\lambda = .55$), but some weaker coefficients (e.g., item B4 $\lambda = .22$) and some stronger coefficients (e.g., item C7 $\lambda = 0.77$).

Table 9: Standardized factor loadings

Factor	Item	Loadings
Attitudes	*"People who work in tech can make a positive difference in the world."*	0.66
Attitudes	*"A tech career would mean working with interesting people."*	0.63
Attitudes	*"Women can do well in tech careers."*	0.35
Attitudes	*"A person's family background would not stop them from having a tech career."*	0.40
Attitudes	*"Tech jobs can create solutions to important challenges we face."*	0.72
Attitudes	*"A tech job would involve doing interesting work."*	0.80
Attitudes	*"There are people from all different cultural backgrounds in the tech industry."*	0.49
Attitudes	*"People who work in tech are respected by others."*	0.54
Attitudes	*"I feel confident I could have a career in tech."*	0.86
Attitudes	*"Most people can have a career in tech, if they want it."*	0.49
Behaviours	*"I think I would be well-suited to a career in tech."*	0.87
Behaviours	*"I plan to look for information about tech careers."*	0.87
Behaviours	*"I am interested in taking tech-related subjects/courses (e.g., maths, science, computer science, design and technology) and/or doing a tech-related apprenticeship."*	0.81
Behaviours	*"I would like to do tech-related work experience."*	0.87
Behaviours	*"In the future, I would consider doing a tech-related degree."*	0.87
Behaviours	*"In the future, I want to apply for jobs in the tech industry."*	0.87
Behaviours	*"I have searched online for education or training that would help me get a career in tech."*	0.67
Behaviours	*"I am/have been a member of a computing/coding/STEM club in or outside of school (STEM: Science, Technology, Engineering, and Maths)."*	0.45

Behaviours	*"I have told my friends/family/carers/teachers that I want to have a career in tech."*	0.79
Behaviours	*"My hobbies and interests are related to tech."*	0.68
Behaviours	*"I have asked for careers advice about how to get into a tech career."*	0.63
Behaviours	*"I have searched tech jobs online."*	0.69
Behaviours	*"I have learnt some tech skills outside of school e.g., coding."*	0.67
Behaviours	*"I have talked to someone who works in tech about their career."*	0.51
Knowledge	*"I can think of several different tech jobs."*	0.73
Knowledge	*"I know what sort of tasks people might do in different tech jobs."*	0.79
Knowledge	*"I know about different types of companies that employ people to do tech jobs."*	0.72
Knowledge	*"I have enough information about tech careers to make decisions about whether I want to go into a tech career."*	0.71
Knowledge	*"I know roughly how much you get paid in different tech jobs."*	0.70
Knowledge	*"I know about which tech jobs are likely to provide opportunities for promotion."*	0.68
Knowledge	*"I don't know much about tech careers."*	0.45
Knowledge	*"I know about courses I could take at school/college after Year 11 that could help me to get a career in tech (e.g., A-levels, T Levels, BTECs)."*	0.64
Knowledge	*"I am aware of the different apprenticeship options for a career in tech."*	0.69
Knowledge	*"I know what sort of degree courses I could study at university to help me to have a career in tech."*	0.74
Knowledge	*"I understand the skills that would be useful for a career in tech."*	0.81
Knowledge	*"I know about the different ways to get into a tech career."*	0.75

Barriers	*"Only the cleverest people can enter tech jobs."*	0.55
Barriers	*"To get a tech job, you need to know someone in the industry."*	0.56
Barriers	*"Tech careers are difficult to get in to."*	0.77
Barriers	*"Tech careers are better suited to men."*	0.40
Barriers	*"You need to go to university to have a career in tech."*	0.52
Barriers	*"I do not have enough information about qualifications that would help me to get into a tech career."*	0.22

Note. Loadings are standardized on the latent-response metric; all $p < .001$

Table 10 presents composite reliability (CR) and average variance extracted (AVE) computed from the standardized solution (Fornell and Larcker, 1981). Attitudes showed CR = .849 and AVE = .376; Knowledge showed CR = .922 and AVE = .499; Behaviours showed CR = .944 and AVE = .554; and Barriers showed CR = .681 and AVE = .282. Table 10 indicates that all four factors demonstrated satisfactory levels of composite reliability, with Knowledge and Behaviours additionally reaching the conventional AVE ≈ .50 benchmark for convergent variance. Table 10 further shows that a Fornell–Larcker discriminant validity check indicated Knowledge (√AVE = .706), Behaviours (√AVE = .744) and Barriers (√AVE = .531) exceeded their inter-factor correlations, supporting discriminant validity, while Attitudes (√AVE = .613) was marginal relative to its correlation with Knowledge (r = .616), consistent with moderate conceptual overlap between attitudinal beliefs and perceived knowledge.

Table 10: Composite Reliability (CR) and Average Variance Extracted (AVE)

Factor	Items (k)	αlpha (ordinal)	ω (McDonald)	CR	AVE	Mean λ	Median λ	Range λ
Attitudes	10	14	0.94	0.85	0.38	0.59	0.584	0.346–0.856
Knowledge	12	10	0.86	0.92	0.50	0.70	0.714	0.454–0.805
Behaviours	14	12	0.92	0.94	0.55	0.73	0.739	0.449–0.873
Barriers	6	6	0.69	0.68	0.28	0.50	0.535	0.223–0.774
Overall	36	36	0.94	-	-	-	-	-

Note. CR = composite reliability, AVE = average variance extracted, k = number of items. Mean, median and range of the standardized loadings are reported for each factor.

Table 11 presents intraclass correlation coefficients (ICCs) for each subscale and for the overall technology scale. Knowledge (ICC = .071) and Attitudes (ICC = .080) reflected modest clustering, with about 7–8% of their variance associated with school-level factors. Behaviours (ICC = .107) and the overall technology scale (ICC = .107) showed similar patterns, with approximately 11% of the variance linked to differences between schools. Barriers showed a smaller ICC (.038), indicating that variation on this subscale was almost exclusively within schools. According to the interpretive guidelines of Koo and (Li, 2016), these coefficients are classified as low in magnitude, while still highlighting that school context contributes in a consistent way across the measures.

Table 11: Intraclass Correlation Coefficients (ICCs) for Subscales and Overall Tech Career Scale

Factor	Between-Cluster Variance	Within-Cluster Variance	ICC	% Variance Between Clusters
Knowledge	13.35	175.33	0.071	7.1%
Attitudes	7.58	87.33	0.080	8.0%
Behaviours	13.35	111.57	0.107	10.7%
Barriers	1.18	29.84	0.038	3.8%
Overall	83.06	693.44	0.107	10.7%

Cronbach's alpha statistics were calculated for the final scales, for their future use. All scales showed satisfactory Cronbach's alpha statistics: Knowledge α = .92, Attitudes α = .86, Behaviours α = .94, Barriers α = .96, overall Tech Career Scale[1] α = .94.

Finally, construct validity was further examined using polychoric correlations between each Tech Career subscale and the validation scale derived from three items asking how likely students were to study maths, science, or technology subjects in the future (Table 12). The results provide encouraging evidence that three of the four subscales, Behaviours, Knowledge, and Attitudes, showed meaningful positive associations with students' intentions to pursue further study in technology-related fields. The Behaviours subscale demonstrated the strongest relationship (r = .54), followed by Attitudes (r = .35) and Knowledge (r = .31). The Barriers subscale showed only a weak association (r = .05), consistent with earlier findings from the exploratory factor analyses.

[1] Overall Tech Career Scale is a score calculated from 36 items and incorporates the Knowledge, Attitudes, and Behaviours subscales only.

Table 12: Confirmatory Convergent Validity: Polychoric Correlations with Validation Scale

Tech Subscale	Validation Scale
Behaviours	0.535
Knowledge	0.313
Attitudes	0.349
Barriers	0.046

4.3 Scoring

The Tech Career Scale is validated for calculation of an overall score – a sum of all items from the Knowledge, Attitudes, and Behaviours subscales – and four individual subscale scores: Knowledge, Attitudes, Behaviours, and Barriers. Due to the very small negative correlations revealed between the Barriers subscale and the other three subscales, the Barriers subscale is not recommended to be incorporated into the overall score calculation. However, the Barriers subscale can be calculated as a standalone subscale: alongside the Tech Career Scale the Barriers subscale may provide useful additional information about students' perceived barriers to pursuing a tech career. Further scoring information is presented in Appendices B and C.

We also examined intra-class correlation coefficients (ICCs), which indicate how much of the variation in students' scores reflects differences between schools or classes rather than between individual students. The ICCs were small to moderate, suggesting that while students in the same school tend to respond somewhat similarly, most differences occur at the individual level (Knowledge = 0.07, Attitudes = 0.08, Behaviours = 0.11, Barriers = 0.04, and overall, Tech Career Scale = 0.11).

To support interpretation of student results, Table 13 summarises approximate 10-percentile bands for the Tech Career Scale and each subscale. Each row shows the corresponding raw-score ranges and an interpretation label (e.g., Low, Average, High). These percentile bands help practitioners understand how a student's score compares with the overall group—for instance, a student at the 70th percentile scored higher than 70 percent of peers. Percentiles are relative to this validation sample and do not yet represent national norms. Percentile bands and raw-score ranges for the Career Knowledge Scale and Personal Skills Scale are provided in Appendix D.

Table 13: Percentile Bands and Raw-Score Ranges for the Tech Career Scale

Percentile Band	Overall Score Range	Knowledge Score Range	Attitudes Score Range	Behaviours Score Range	Barriers Score Range	Interpretation
0–9	≤108	≤27	≤34	≤13	≤17	Very Low
10–19	109–118	28–35	35–38	14–17	18–20	Below Average
20–29	119–128	36–40	39–41	18–21	21–23	Slightly Below Average
30–39	129–135	41–44	42–44	22–24	24–26	Average
40–49	136–142	45–47	45–47	25–26	27–28	Average
50–59	143–149	48–50	48–50	27–29	29–30	Average
60–69	150–156	51–55	51–53	30–32	31–32	Average
70–79	157–163	56–59	54–56	33–35	33–34	Slightly Above Average
80–89	164–172	60–64	57–60	36–39	35–37	Above Average
90–99	≥173	≥65	≥61	≥40	≥38	Very High

The final version of the Tech Career Scale is shown in Appendix C (Table C1), with item-level descriptive statistics in Appendix B (Table B1).

Conclusion

This study reports the development and validation of the Tech Career Scale, a 42-item self-report instrument measuring Knowledge (12 items), Attitudes (10 items), Behaviours (14 items) and Barriers (6 items) towards careers in tech. Across two datasets, factor analyses of the Tech Career Scale have supported a coherent four-factor structure, as well as acceptable-excellent reliability estimates on individual subscales and for the overall scale. The model for the scale demonstrates acceptable approximation to the data for a large ordinal instrument, strong standardized loadings, high composite reliability, and coherent factor correlations. In combination with the evidence showing moderate to high correlations with intention to choose tech-compatible A Level courses, these findings support computing individual subscale scores for Attitudes, Knowledge, Behaviours, and Barriers. The results also support computing an overall score for Knowledge, Attitudes, and Behaviours items. The final version of the Tech Career Scale and item level descriptive statistics are included in the appendices of this report.

To support consistent and appropriate use of the Tech Career Scale, several good practice principles are recommended. The full set of items for each subscale should be administered, and items should not be dropped or modified, as this would affect reliability and comparability. Scoring should follow the procedures and lookup tables provided in this report to ensure consistent handling of Likert-type and binary items. Scores should be calculated and reported at the subscale level in the first instance. Where an overall score is required, it should be computed using the Knowledge, Attitudes, and Behaviours subscales only, with the Barriers subscale used optionally when there is a specific interest in perceived obstacles to pursuing tech careers.

The measure is freely available for use by The Hg Foundation’s partners and any organisations working to ensure the tech-workforce of the future harnesses the talents of all, regardless of background. The Tech Career Scale could have utility in a range of different study designs, including to measure change in knowledge, attitudes, and behaviours towards tech careers.

Appendix A: Development and Validation of the Career Knowledge Scale and Personal Skills Scale.

The Career Knowledge and Personal Skills scales were developed and validated using the same statistical methods as the Tech Career Scale. Selected items from the Future Skills Questionnaire (FSQ; Tanner and Finlay, 2021) were adapted to create the Career Knowledge Scale – items were adapted to have a first-person perspective, wording was altered to improve clarity, and the response scale changed to a scale of agreement. The Personal Skills scale items were written using inspiration from the Essential Skills for Life and Work section of the FSQ, and the Skills Builder Universal Framework 2.0 (Ravenscroft and Baker, 2020). Their intended use is in an evaluation that will also utilise the Tech Career Scale so it made sense to use the same samples of pupils to evaluate them. However, they do not form part of the overall scale and could be used independently if required.

Career Knowledge Scale

Phase 1: Exploratory Factor Analysis

KMO measure of sampling adequacy was 0.88, which falls in the range and indicates substantial common variance suitable for factor analysis (Kaiser, 1974). Bartlett's test of sphericity was significant, χ^2 (28) = 1465.69, $p < .001$, rejecting the null hypothesis that the correlation matrix is an identity matrix and confirming that the items share enough variance for factoring (Bartlett, 1950). Together these results supported the suitability of the data for exploratory factor analysis. Through evaluation of the factor loadings (Table A1) and scree plot (Figure A1), it was determined that a one-factor solution was in fact the best fit for the data. The results of the exploratory factor analysis supported a coherent one-factor structure, in line with predictions, and therefore no item changes were necessary.

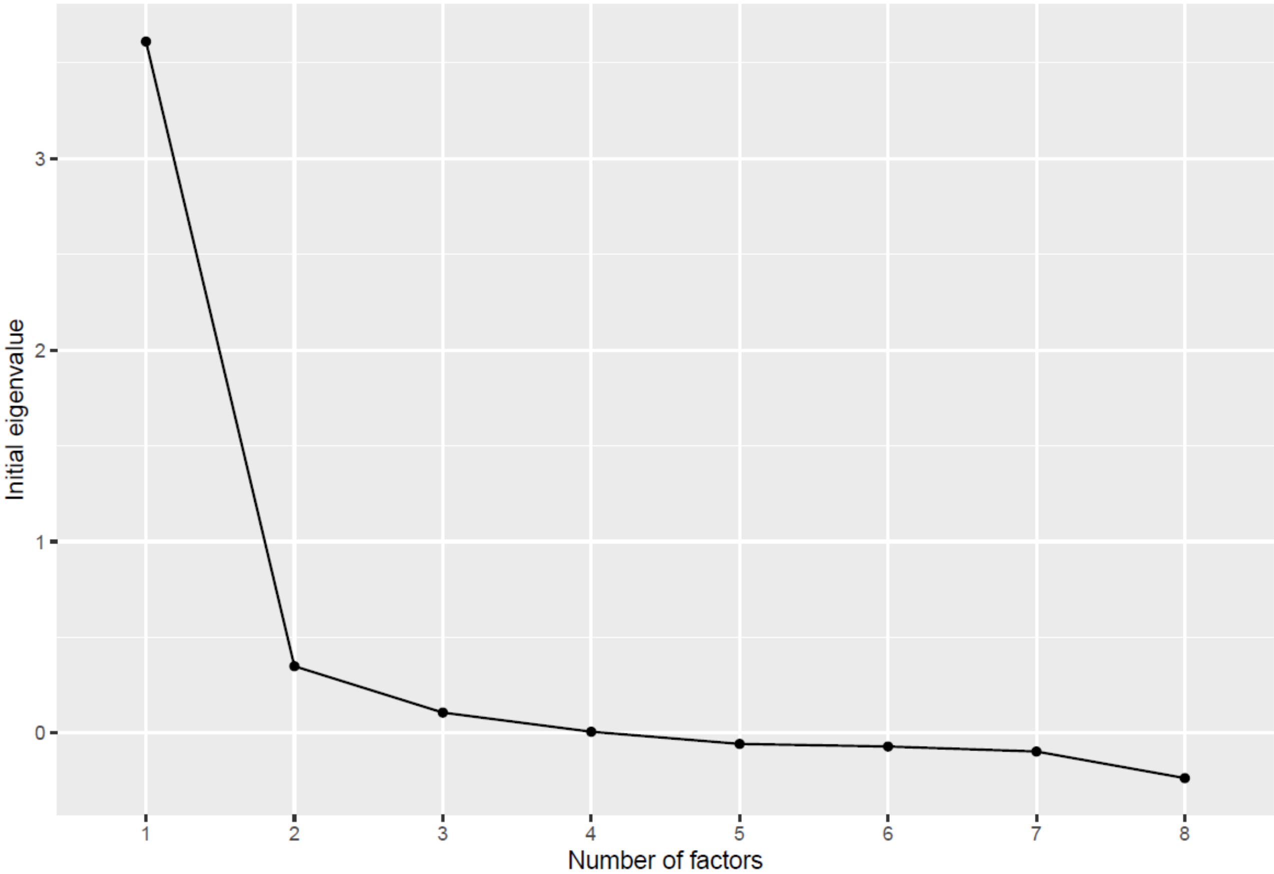
Table A1: Factor Loadings

Item	Item Text	Factor 1	KMO	Communality
1	I have heard people other than my family or carers talk about their jobs.	0.66	0.83	0.43
2	I know about some types of businesses/employers in my local area.	0.63	0.89	0.40
3	I know how to find out how much money you can make in different types of jobs.	0.73	0.89	0.53
4	I have support to help me make education and career choices.	0.67	0.91	0.45
5	I know about some trustworthy websites I can use to help me decide what to do in the future.	0.64	0.87	0.40

6	I know what kinds of jobs or careers would fit my interests or skills.	0.73	0.89	0.53
7	I know how to make a good impression when applying for a course or job.	0.72	0.90	0.51
8	I have a plan for my next step after Year 11.	0.59	0.88	0.35

Note. Items were scored on a 7-point Likert scale of agreement. Factor 1 reports the factor loadings of the first factor.

Figure A1: Scree plot of the Career Knowledge Scale.



Phase 2: Confirmatory Factor Analysis and Reliability

In the second phase of the study, in an independent sample, confirmatory factor analysis confirmed the one-factor structure of the Career Knowledge Scale. Fit indices were within or close to the critical range: χ^2 (20) = 1447.01 (scaled), CFI = .909, TLI = .873, RMSEA = .182 (90% CI [.174, .190]), and SRMR = .058, and all factor loadings were strong (Table A2), suggesting a coherent one-factor structure.

Table A2: Standardized factor loadings

Item	*Item Text*	Loadings
1	*I have heard people other than my family or carers talk about their jobs.*	0.67
2	*I know about some types of businesses/employers in my local area.*	0.71
3	*I know how to find out how much money you can make in different types of jobs.*	0.76
4	*I have support to help me make education and career choices.*	0.76
5	*I know about some trustworthy websites I can use to help me decide what to do in the future.*	0.72
6	*I know what kinds of jobs or careers would fit my interests or skills.*	0.77
7	*I know how to make a good impression when applying for a course or job.*	0.75
8	*I have a plan for my next step after Year 11.*	0.65

Note. Loadings are standardized on the latent-response metric; all $p < .001$

Reliability indices for the Career Knowledge Scale were (α =0.89 , ω = 0.92). Scores range from 8-56, with higher scores indicating greater career knowledge. The final scale is shown in Table A3.

Table A3. Career Knowledge Scale

<table>
<tr><th colspan="4">Career Knowledge Scale</th></tr>
<tr><td colspan="4">These questions will ask you about your career knowledge. For these questions, please think about ALL careers you may know about or be interested in</td></tr>
<tr><td>Item Number</td><td>Item</td><td>Reverse Scoring</td><td>Scale</td></tr>
<tr><td>1</td><td>I have heard people other than my family or carers talk about their jobs.</td><td></td><td rowspan="3">On a scale of 1 (Strongly Disagree) to 7 (Strongly Agree) please tell us how much you agree with the following statements.
1=Strongly Disagree
Disagree</td></tr>
<tr><td>2</td><td>I know about some types of businesses/employers in my local area.</td><td></td></tr>
<tr><td>3</td><td>I know how to find out how much money you can make in different types of jobs.</td><td></td></tr>
</table>

4	I have support to help me make education and career choices.	3=Slightly Disagree 4=Neither Agree nor Disagree 5=Slightly Agree 6=Agree 7=Strongly Agree
5	I know about some trustworthy websites I can use to help me decide what to do in the future.	
6	I know what kinds of jobs or careers would fit my interests or skills.	
7	I know how to make a good impression when applying for a course or job.	
8	I have a plan for my next step after Year 11.	

Note. Scores range from 8-56, with higher scores indicating greater career knowledge.

Personal Skills Scale

Phase 1: Exploratory Factor Analysis

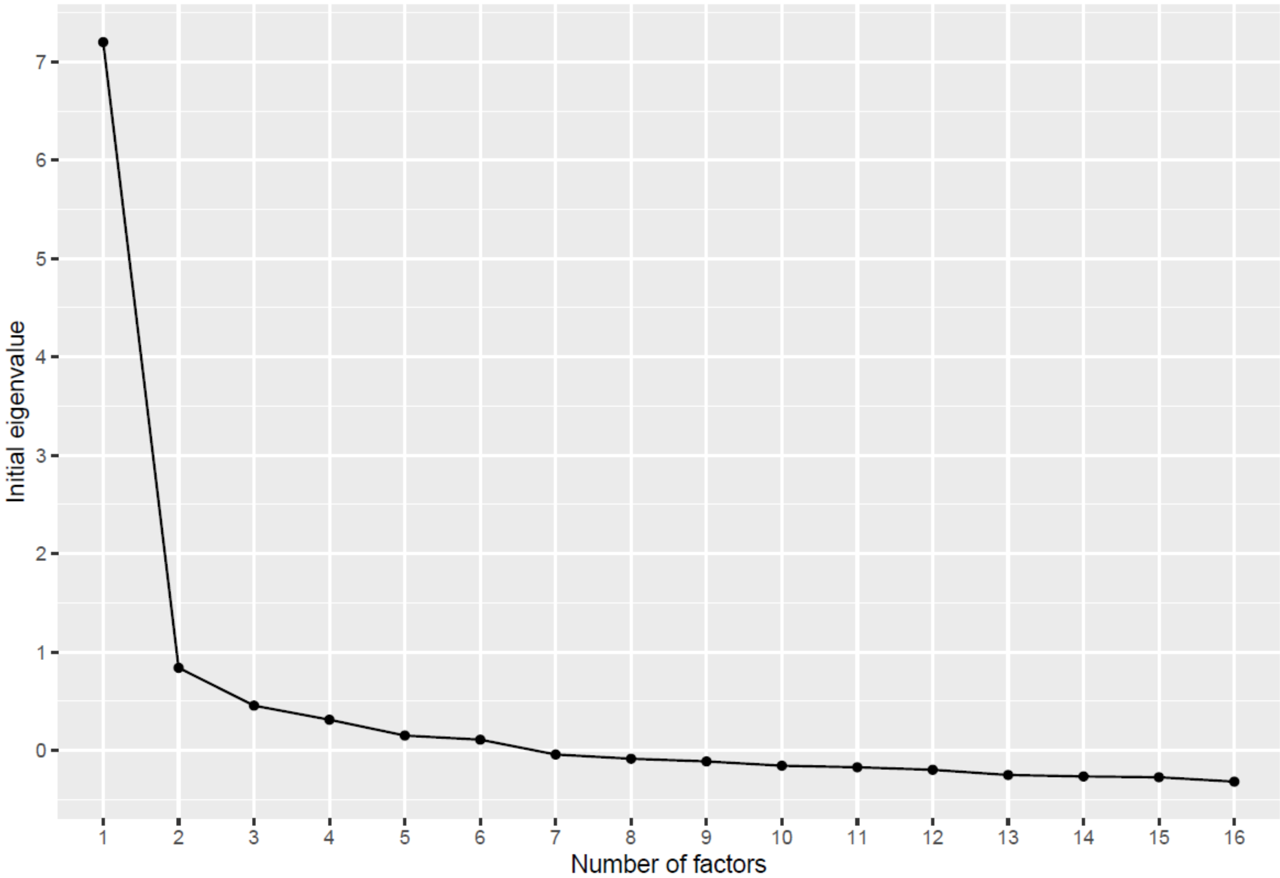
KMO measure of sampling adequacy was 0.93, which falls in the range and indicates substantial common variance suitable for factor analysis (Kaiser, 1974). Bartlett's test of sphericity was significant, $\chi^2(120) = 4204.12$, $p < .001$, rejecting the null hypothesis that the correlation matrix is an identity matrix and confirming that the items share enough variance for factoring (Bartlett, 1950). Together these results supported the suitability of the data for exploratory factor analysis. Through evaluation of the factor loadings (Table A4) and scree plot (Figure A2), it was determined that a one-factor solution was in fact the best fit for the data. The results of the exploratory factor analysis supported a coherent one-factor structure, in line with predictions. On revision of the scale one additional item was added for the second phase "I try different ways to reach my goals even when I face challenges".

Table A4: Factor Loadings

Item	*Item Text*	Factor 1	KMO	Communality
1	I can usually listen to and remember things I have been told.	0.65	0.94	0.42
2	I am aware of how a speaker is trying to influence others by the way they speak.	0.66	0.92	0.44
3	I can share my ideas clearly and confidently.	0.68	0.93	0.47
4	I can adapt what I say depending on the response of listeners.	0.72	0.94	0.52
5	I can find solutions to problems I experience.	0.72	0.94	0.51
6	I will test different ideas to solve complex tasks.	0.71	0.94	0.51
7	I am good at thinking of new ideas.	0.68	0.90	0.47
8	I can come up with new or different ways of doing things.	0.71	0.90	0.51
9	I stay positive when I experience difficulties.	0.57	0.93	0.33
10	I can identify the positives and negatives in an opportunity.	0.66	0.93	0.43
11	I aim high and often succeed in what I aim for.	0.70	0.94	0.49
12	To achieve my goals, I make plans with clear targets.	0.65	0.94	0.43
13	When working in a group I often take the lead.	0.59	0.89	0.34
14	When working in a group I often support others through mentoring or coaching.	0.63	0.91	0.40
15	I work well with others and finish my parts of group tasks.	0.70	0.94	0.49
16	I can help to resolve disagreements in a team.	0.67	0.93	0.45

Note. Items were scored on a 7-point Likert scale of agreement. Factor 1 reports the factor loadings of the first factor.

Figure A2: Scree plot of the Personal Skills Scale.



Phase 2: Confirmatory Factor Analysis and Reliability

In the second phase of the study, in an independent sample, confirmatory factor analysis confirmed the one-factor structure of the Career Knowledge Scale. Fit indices were within or close to the critical range: χ^2 (119) = 5134.479 (scaled), CFI = .88, TLI = .863, RMSEA = .141 (90% CI [.138, .144]), and SRMR = .061, and all factor loadings were strong (Table E), suggesting a coherent one-factor structure.

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Table A5: Standardized factor loadings

Item	Item Text	Loadings
1	I can usually listen to and remember things I have been told.	0.68
2	I am aware of how a speaker is trying to influence others by the way they speak.	0.71
3	I can share my ideas clearly and confidently.	0.74
4	I can adapt what I say depending on the response of listeners.	0.75
5	I can find solutions to problems I experience.	0.79
6	I will test different ideas to solve complex tasks.	0.76
7	I am good at thinking of new ideas.	0.73
8	I can come up with new or different ways of doing things.	0.76
9	I stay positive when I experience difficulties.	0.62
10	I can identify the positives and negatives in an opportunity.	0.77
11	I aim high and often succeed in what I aim for.	0.77
12	I try different ways to reach my goals even when I face challenges.	0.81
13	To achieve my goals, I make plans with clear targets.	0.71
14	When working in a group I often take the lead.	0.65
15	When working in a group I often support others through mentoring or coaching.	0.71
16	I work well with others and finish my parts of group tasks.	0.75
17	I can help to resolve disagreements in a team.	0.73

Note. Loadings are standardized on the latent-response metric; all $p < .001$

Reliability indices for the Personal Skills Scale were (α =0.95 , ω = 0.96). Scores range from 17-117, with higher scores indicating greater personal skills. The final scale is shown in Table A7.

To support the interpretation of scores Table A6 gives the percentile band ranges for the two scales along with a descriptive interpretation.

Table A6: Percentile Bands and Raw-Score Ranges for the Career Knowledge and Personal Skills Scales

Percentile Band	Career Knowledge	Personal Skills	Interpretation
0–9	≤27	≤60	Very Low / Low
10–19	28–31	61–67	Below Average
20–29	32	68–70	Below Average–Average
30–39	33–35	71–76	Average
40–49	36–38	77–81	Average
50–59	39–40	82–85	Average–Above Avg
60–69	41–43	86–90	Above Average
70–79	44–46	91–95	High
80–89	47–49	96–102	High
90–99	≥50	≥103	Very High

Table A7: Personal Skills Scale

<table>
<tr><th colspan="4">Personal Skills Scale</th></tr>
<tr><td colspan="4">These questions will ask you about your personal skills.</td></tr>
<tr><td>Item Number</td><td>Item</td><td>Reverse Scoring</td><td>Scale</td></tr>
<tr><td>1</td><td>I can usually listen to and remember things I have been told.</td><td></td><td rowspan="17">On a scale of 1 (Strongly Disagree) to 7 (Strongly Agree) please tell us how much you agree with the following statements.
1=Strongly Disagree
2=Disagree
3=Slightly Disagree
4=Neither Agree nor Disagree
5=Slightly Agree
6=Agree
7=Strongly Agree</td></tr>
<tr><td>2</td><td>I am aware of how a speaker is trying to influence others by the way they speak.</td><td></td></tr>
<tr><td>3</td><td>I can share my ideas clearly and confidently.</td><td></td></tr>
<tr><td>4</td><td>I can adapt what I say depending on the response of listeners.</td><td></td></tr>
<tr><td>5</td><td>I can find solutions to problems I experience.</td><td></td></tr>
<tr><td>6</td><td>I will test different ideas to solve complex tasks.</td><td></td></tr>
<tr><td>7</td><td>I am good at thinking of new ideas.</td><td></td></tr>
<tr><td>8</td><td>I can come up with new or different ways of doing things.</td><td></td></tr>
<tr><td>9</td><td>I stay positive when I experience difficulties.</td><td></td></tr>
<tr><td>10</td><td>I can identify the positives and negatives in an opportunity.</td><td></td></tr>
<tr><td>11</td><td>I aim high and often succeed in what I aim for.</td><td></td></tr>
<tr><td>12</td><td>I try different ways to reach my goals even when I face challenges.</td><td></td></tr>
<tr><td>13</td><td>To achieve my goals, I make plans with clear targets.</td><td></td></tr>
<tr><td>14</td><td>When working in a group I often take the lead.</td><td></td></tr>
<tr><td>15</td><td>When working in a group I often support others through mentoring or coaching.</td><td></td></tr>
<tr><td>16</td><td>I work well with others and finish my parts of group tasks.</td><td></td></tr>
<tr><td>17</td><td>I can help to resolve disagreements in a team.</td><td></td></tr>
</table>

Note. Scores range from 17-117, with higher scores indicating greater personal skills.

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Appendix B: Descriptive statistics

Table B1. Item-level descriptive statistics

Factor	Item	Observed Range	Mean	SD
Attitudes	*“People who work in tech can make a positive difference in the world.”*	1 - 7	4.852	1.421
Attitudes	*“A tech career would mean working with interesting people.”*	1 - 7	4.224	1.406
Attitudes	*“Women can do well in tech careers.”*	1 - 7	5.69	1.559
Attitudes	*“A person’s family background would not stop them from having a tech career.”*	1 - 7	4.635	1.657
Attitudes	*“Tech jobs can create solutions to important challenges we face.”*	1 - 7	4.888	1.403
Attitudes	*“A tech job would involve doing interesting work.”*	1 - 7	4.503	1.49
Attitudes	*“There are people from all different cultural backgrounds in the tech industry.”*	1 - 7	5.281	1.485
Attitudes	*“People who work in tech are respected by others.”*	1 - 7	4.363	1.262
Attitudes	*“I feel confident I could have a career in tech.”*	1 - 7	3.634	1.778
Attitudes	*“Most people can have a career in tech, if they want it.”*	1 - 7	4.726	1.49
Behaviours	*“I think I would be well-suited to a career in tech.”*	1 - 7	3.391	1.79
Behaviours	*“I plan to look for information about tech careers.”*	1 - 7	3.296	1.753
Behaviours	*“I am interested in taking tech-related subjects/courses (e.g., maths, science, computer science, design and technology) and/or doing a tech-related apprenticeship.”*	1 - 7	3.739	1.907
Behaviours	*“I would like to do tech-related work experience.”*	1 - 7	3.41	1.806

Behaviours	*"In the future, I would consider doing a tech-related degree."*	1 - 7	3.32	1.768
Behaviours	*"In the future, I want to apply for jobs in the tech industry."*	1 - 7	3.357	1.8
Behaviours	*"I have searched online for education or training that would help me get a career in tech."*	0 - 1	0.191	0.393
Behaviours	*"I am/have been a member of a computing/coding/STEM club in or outside of school (STEM: Science, Technology, Engineering, and Maths)."*	0 - 1	0.189	0.391
Behaviours	*"I have told my friends/family/carers/teachers that I want to have a career in tech."*	0 - 1	0.215	0.411
Behaviours	*"My hobbies and interests are related to tech."*	0 - 1	0.371	0.483
Behaviours	*"I have asked for careers advice about how to get into a tech career."*	0 - 1	0.151	0.358
Behaviours	*"I have searched tech jobs online."*	0 - 1	0.228	0.42
Behaviours	*"I have learnt some tech skills outside of school e.g., coding."*	0 - 1	0.292	0.455
Behaviours	*"I have talked to someone who works in tech about their career."*	0 - 1	0.355	0.478
Knowledge	*"I can think of several different tech jobs."*	1 - 7	4.598	1.627
Knowledge	*"I know what sort of tasks people might do in different tech jobs."*	1 - 7	4.398	1.529
Knowledge	*"I know about different types of companies that employ people to do tech jobs."*	1 - 7	4.305	1.621
Knowledge	*"I have enough information about tech careers to make decisions about whether I want to go into a tech career."*	1 - 7	3.97	1.695
Knowledge	*"I know roughly how much you get paid in different tech jobs."*	1 - 7	3.294	1.648

Knowledge	*"I know about which tech jobs are likely to provide opportunities for promotion."*	1 - 7	3.227	1.6
Knowledge	*"I don't know much about tech careers."*	1 - 7	3.83	1.792
Knowledge	*"I know about courses I could take at school/college after Year 11 that could help me to get a career in tech (e.g., A-levels, T Levels, BTECs)."*	1 - 7	4.24	1.727
Knowledge	*"I am aware of the different apprenticeship options for a career in tech."*	1 - 7	3.638	1.615
Knowledge	*"I know what sort of degree courses I could study at university to help me to have a career in tech."*	1 - 7	3.667	1.621
Knowledge	*"I understand the skills that would be useful for a career in tech."*	1 - 7	4.408	1.57
Knowledge	*"I know about the different ways to get into a tech career."*	1 - 7	3.68	1.553
Barriers	*"Only the cleverest people can enter tech jobs."*	1 - 7	4.872	1.603
Barriers	*"To get a tech job, you need to know someone in the industry."*	1 - 7	5.209	1.419
Barriers	*"Tech careers are difficult to get in to."*	1 - 7	3.557	1.28
Barriers	*"Tech careers are better suited to men."*	1 - 7	3.391	1.79
Barriers	*"You need to go to university to have a career in tech."*	1 - 7	4.231	1.463
Barriers	*"I do not have enough information about qualifications that would help me to get into a tech career."*	1 - 7	3.832	1.594

Table B2. Scale level descriptive statistics

Scale	N	Mean	SD	Median	Q1	Q3	Min	Max
Knowledge	2181	47.07	13.7	48	38	56	12	84
Attitudes	2181	46.63	9.7	47	41	53	10	70
Behaviours	2181	22.46	11.1	23	13	30	3	50
Barriers	2181	26.72	5.5	27	24	30	6	42
Overall	2181	142.8	27.7	141	124	161	64	236

To assess the degree to which responses varied between schools, intraclass correlation coefficients (ICCs) were calculated for each subscale and for the overall Tech Career Scale composite score. ICCs represent the proportion of total variance attributable to between-school differences. In educational survey contexts, values <0.05 are typically considered very small, 0.05–0.15 modest, and values ≥ 0.15 indicative of moderate clustering (Snijders, and Bosker, 2012).

ICCs for the four Tech Career Scale subscales ranged from very small to moderate: Knowledge (ICC = 0.07), Attitudes (ICC = 0.08), Behaviours (ICC = 0.11), and Barriers (ICC = 0.04). The overall composite ICC was 0.11, reflecting a modest degree of clustering when all items are combined. For the two additional scales used in the evaluation, Personal Skills had an ICC of 0.05 and Career Knowledge an ICC of 0.03. Taken together, these values indicate that although there is some clustering at the school level, particularly for the overall composite and the Behaviours subscale, most of the variance is attributable to individual differences.

Appendix C: Tech Career Scale final version

Table C1. Final version of the Tech Career Scale

Tech Career Scale				
In this survey you will be asked questions relating to 'careers in tech'. There are many different careers in tech, including: data analytics, programming and working with code, cyber security, artificial intelligence (AI), digital marketing, gaming, technology research, software development, and IT support, to name a few.				
Knowledge				
Item Number	**Item Number in Analysis**	**Item**	**Reverse Scoring**	**Scale**
1	A1	I can think of several different tech jobs.		*On a scale of 1 (Strongly Disagree) to 7 (Strongly Agree) please tell us how much you agree with the following statements.* 1=Strongly Disagree 2=Disagree 3=Slightly Disagree 4=Neither Agree nor Disagree 5=Slightly Agree 6=Agree 7=Strongly Agree
2	A2	I know what sort of tasks people might do in different tech jobs.		
3	A3	I know about different types of companies that employ people to do tech jobs.		
4	A4	I have enough information about tech careers to make decisions about whether I want to go into a tech career.		
5	A5	I know roughly how much you get paid in different tech jobs.		
6	A6	I know about which tech jobs are likely to provide opportunities for promotion.		
7	A7	I don't know much about tech careers.	Reverse scored	
8	B1	I know about courses I could take at school/college after Year 11 that could help me to get a career in tech (e.g., A-levels, T Levels, BTECs).		
9	B2	I am aware of the different apprenticeship options for a career in tech.		

10	B3	I know what sort of degree courses I could study at university to help me to have a career in tech.		
11	B5	I understand the skills that would be useful for a career in tech.		
12	B6	I know about the different ways to get into a tech career.		
Knowledge subscale total score ranges from 12-84, in which higher scores indicate greater knowledge.				
Attitudes				
13	C3	People who work in tech can make a positive difference in the world.		*On a scale of 1 (Strongly Disagree) to 7 (Strongly Agree) please tell us how much you agree with the following statements.* 1=Strongly Disagree 2=Disagree 3=Slightly Disagree 4=Neither Agree nor Disagree 5=Slightly Agree 6=Agree 7=Strongly Agree
14	C5	A tech career would mean working with interesting people.		
15	C6	Women can do well in tech careers.		
16	C8	A person's family background would not stop them from having a tech career.		
17	C9	Tech jobs can create solutions to important challenges we face.		
18	C10	A tech job would involve doing interesting work.		
19	C12	There are people from all different cultural backgrounds in the tech industry.		
20	C14	People who work in tech are respected by others.		
21	C15	I feel confident I could have a career in tech.		
22	C16	Most people can have a career in tech, if they want it.		
Attitudes subscale total score ranges from 10-70, in which higher scores indicate more positive attitudes.				
Behaviours				
23	D1	I think I would be well-suited to a career in tech.		*On a scale of 1 (Strongly Disagree)*

24	D2	I plan to look for information about tech careers.		*to 7 (Strongly Agree) please tell us how much you agree with the following statements.* 1=Strongly Disagree Disagree 3=Slightly Disagree 4=Neither Agree nor Disagree 5=Slightly Agree 6=Agree 7=Strongly Agree
25	D3	I am interested in taking tech-related subjects/courses (e.g., maths, science, computer science, design and technology) and/or doing a tech-related apprenticeship.		
26	D4	I would like to do tech-related work experience.		
27	D5	In the future, I would consider doing a tech-related degree.		
28	D6	In the future, I want to apply for jobs in the tech industry.		
29	E1	I have searched online for education or training that would help me get a career in tech.	Reverse scored	Please respond 'Yes' or 'No' to the following statements. 0=Yes 1=No
30	E2	I am/have been a member of a computing/coding/STEM club in or outside of school (STEM: Science, Technology, Engineering, and Maths).	Reverse scored	
31	E3	I have told my friends/family/carers/teachers that I want to have a career in tech.	Reverse scored	
32	E4	My hobbies and interests are related to tech.	Reverse scored	
33	E5	I have asked for careers advice about how to get into a tech career.	Reverse scored	
34	E6	I have searched tech jobs online.	Reverse scored	
35	E7	I have learnt some tech skills outside of school e.g., coding.	Reverse scored	
36	E8	I have talked to someone who works in tech about their career.	Reverse scored	
Behaviours subscale total score ranges from 6-50, in which higher scores indicate greater self-reported behaviours/intentions.				

<table>
<tr><td colspan="5">An overall Tech Career Scale score, combining the Knowledge, Attitudes and Behaviours subscales, can be calculated. Scores range from 28-207, with higher scores indicating greater knowledge, attitudes and behaviours towards tech careers.</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td colspan="5">Barriers</td></tr>
<tr><td>37</td><td>C1</td><td>Only the cleverest people can enter tech jobs.</td><td></td><td rowspan="6">On a scale of 1 (Strongly Disagree) to 7 (Strongly Agree) please tell us how much you agree with the following statements.
1=Strongly Disagree
2=Disagree
3=Slightly Disagree
4=Neither Agree nor Disagree
5= Slightly Agree
6=Agree
7=Strongly Agree</td></tr>
<tr><td>38</td><td>C2</td><td>To get a tech job, you need to know someone in the industry.</td><td></td></tr>
<tr><td>39</td><td>C7</td><td>Tech careers are difficult to get in to.</td><td></td></tr>
<tr><td>40</td><td>C11</td><td>Tech careers are better suited to men.</td><td></td></tr>
<tr><td>41</td><td>C4</td><td>You need to go to university to have a career in tech.</td><td></td></tr>
<tr><td>42</td><td>B4</td><td>I do not have enough information about qualifications that would help me to get into a tech career.</td><td></td></tr>
<tr><td colspan="5">Barriers subscale total score ranges from 6-42, in which higher scores indicate high perceptions of barriers. Note that this scale should not be included in the calculation of the overall Tech Career Scale score.</td></tr>
</table>

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