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Impulsivity and self-reported driving behaviour among Chinese employee drivers: testing personal innovativeness in IT as a moderator

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Abstract

Impulsivity is associated with self-reported driving behaviour, but it is unclear whether a general willingness to try information technology identifies differences in those associations. Personal innovativeness in IT (PIIT) is a distal technology-adoption orientation rather than a measure of digital engagement while driving. This post hoc, focused, cross-sectional secondary analysis examined a fixed archive of 492 employee private-car commuters from 16 cities in Shandong Province, China. Primary gender-adjusted models included 490 participants. Identical hierarchical regressions examined Mixed Errors and Violations, Lapses and Aggressive Violations, adjusting for age, gender and driving experience. Scores were reconstructed from raw questionnaire items. HC3 standard errors supported coefficient inference, with Holm adjustment applied separately to three-test families of impulsivity coefficients, PIIT coefficients and interactions. The thesis-derived impulsivity composite was positively associated with all three outcomes (B = 0.262, 0.413 and 0.282; standardised β = .274, .372 and .247; all Holm-adjusted ps < .001). Corresponding Impulsivity × PIIT raw ps were .374, .629 and .332; all interaction-family Holm-adjusted ps were .995. No PIIT interaction remained supported after robust inference and familywise correction. Broader and distribution-sensitive specifications did not materially change this conclusion. These findings concern inherited self-report content scores, not independently confirmed driving dimensions or objective safety outcomes. The two-item PIIT-derived measure cannot represent behaviour-specific technology engagement. Its limited coverage and conflicting anchor records constrain interpretation; the results establish neither equivalence nor the irrelevance of digital behaviour. Future studies should measure specific technologies, functions and timing directly. No educational or behavioural intervention was implemented or evaluated.

Introduction

Self-regulation during driving involves withholding rapid responses and maintaining attention to the current task. Impulsivity describes dispositions towards rapid or insufficiently considered action. Associations with driving self-reports have been observed in Chinese and international samples, although findings depend on the facets and behavioural content assessed (Ge et al., 2020; Pearson et al., 2013). The Driver Behaviour Questionnaire (DBQ) distinguishes failures of attention or action from deliberate departures from accepted practices (Reason et al., 1990). Examining several content scores can preserve these distinctions. DBQ responses describe perceived behavioural tendencies rather than crash or injury records, even when they correlate with accidents (de Winter and Dodou, 2010; Useche et al., 2022).

Impulsivity is multidimensional: urgency concerns rash action in emotional contexts, whereas sensation seeking and limited planning capture different tendencies (Cyders et al., 2007; Cyders and Smith, 2008). The source thesis retained an empirical composite dominated by urgency-related items but containing one item with restlessness or sensation-seeking provenance. We retain the label thesis-derived impulsivity composite with substantial urgency-related content rather than equating it with pure Positive Urgency. The three inherited driving scores, Mixed Errors and Violations, Lapses, and Aggressive

Violations, likewise preserve the parent study's scoring history without assuming independent confirmation of three latent dimensions.

Personal innovativeness in IT (PIIT) concerns a general willingness to try new information technologies (Agarwal and Prasad, 1998), an orientation studied in technology acceptance (Jackson et al., 2013). Its scope differs from phone use, message responding, notification exposure, task timing, navigation use, digital skill and actual device engagement during a driving episode. Mostyn Sullivan et al. (2021) examined phone involvement and driving-related phone use, whereas Qu et al. (2020) assessed WeChat use. Truelove et al. (2025) distinguished reading, writing, talking and media use alongside phone dependence. Such behaviour-specific measurements cannot be inferred from a PIIT score.

The moderation question concerns whether a broad adoption orientation distinguishes the association between impulsivity and reported road behaviour. A willingness to experiment might accompany competing demands, but could also coexist with advance preparation; neither process was measured here. Research on attention and self-regulation shows why the setting and task need direct assessment (Love et al., 2022; Love et al., 2025; Young et al., 2024). Zhang et al. (2023), for example, distinguished calling from WeChat messaging and active from responsive use in a simulator. A PIIT score cannot identify those activities. Testing its interaction with impulsivity evaluates whether the available distal measure is informative about differences in driving self-reports, while leaving the specific digital processes to studies that measure them.

The Present Study

Two evaluative questions guide this focused secondary analysis. RQ1 asks whether the thesis-derived impulsivity composite is associated with Mixed Errors and Violations, Lapses and Aggressive Violations after adjustment for age, gender, driving experience and PIIT. RQ2 asks whether those adjusted associations vary by the thesis-retained two-item PIIT score. The parent-study findings were already known, so these are post hoc questions rather than preregistered prospective hypotheses. Applying the same specification to each outcome allows consistent comparison. The study examines the limits of using a general technology-adoption orientation to interpret driving behaviour; it is not an independent replication or a test of a specific digital mechanism.

Methods

Participants and Procedure

This was a post hoc, focused cross-sectional secondary analysis of a previously analysed doctoral survey archive. The source was a doctoral thesis submission manuscript; it is described here as study provenance rather than a publicly available literature reference. The source study surveyed currently employed adults in Shandong Province who held a valid Chinese driving licence and personally drove a private four-wheeled car as their main mode of travel between home and work. Eligible respondents

drove to work at least once per week and reported a typical one-way commute of at least 15 minutes. Professional or commercial drivers, fully remote workers without regular commuting, unemployed respondents, and people whose principal commuting mode was not a private car were outside the target population. The survey was administered once from May through October 2024. The thesis describes voluntary participation, anonymous electronic responses, and linguistic preparation involving forward translation, reconciliation, back-translation, bilingual review, and a pilot study (Beaton et al., 2000; Brislin, 1970). Those procedures supported questionnaire preparation but did not independently validate every adapted score.

The source thesis describes city-stratified recruitment through formally registered work units across 16 cities. The analytic archive did not include the work-unit lists, selection records, selection probabilities, sampling weights, cluster identifiers, or a complete case-level screening ledger. The implementation of the probability-sampling procedure described in the source thesis could not be independently verified from the archived records available for this secondary analysis. Probability-based population estimates are therefore not reported. The thesis records 1,000 invitations, 668 returned questionnaires, and 176 exclusions, leaving the fixed 492-case archive; the excluded returns were unavailable for reconstruction. Although eligibility concerned employee private-car commuting, the DBQ items asked about general road behaviour rather than a particular commuting trip. Because work-unit identifiers were unavailable in the archived analytic file, standard errors could not be adjusted for potential clustering within work units. Participant characteristics and analytic samples are summarised in Table 1.

Table 1
Participant characteristics and analytic samples

Characteristic	n or M (SD)	Details
Invited / returned / excluded	1000 / 668 / 176	Thesis flow; exclusions not recoverable
Archive / primary models	492 / 490	HC3 estimability rule
Age, years	43.86 (6.76)	Range 21–68
Female response category	264 (53.7%)	Full archive
Male response category	226 (45.9%)	Full archive
Nonbinary response category	1 (0.2%)	Full archive
Prefer not to say	1 (0.2%)	Full archive
Driving experience, years	13.87 (6.72)	Range 1–39

Note. N = 492 for characteristics. Primary gender-adjusted models include the 490 participants selecting male or female. No case was classified as invalid. Recruitment was May–October 2024. Minimum observed experience was not an eligibility rule.

Gender was recorded as male (n = 226), female (n = 264), nonbinary (n = 1), or prefer not to say (n = 1). Separate indicators for the singleton categories gave those observations leverage of 1 in a fully coded model, so HC3 standard errors were not stably estimable. Primary gender-adjusted models included the

490 participants who selected the male or female response category; a fixed sensitivity retained all 492 cases and omitted gender. Neither case was classified as invalid. Descriptive and measurement analyses used all 492 cases. Quality flags were used only in sensitivity analyses.

Measures

Impulsivity

Impulsivity was reconstructed as the mean of Q12–Q23 and Q26. All retained items were scored in the same direction under the adopted source scoring rule; no reverse coding was applied. Because Q26 originated in restlessness or sensation-seeking material, the 13-item score is described as a thesis-derived impulsivity composite with substantial urgency-related content. In the full archive, M = 2.32, SD = 0.66, Cronbach's α = .939, and one-factor ω = .941. Supplementary Information, Table A1 gives the exact formula, item sources, missing-data rule, and reliability; Supplementary Information, Table A2 provides the item-level audit.

Personal Innovativeness in IT

The available two-item PIIT-derived score was the mean of Q153 and Q154, retained from the parent study's four-item block. The items concern being early among peers to try new information technologies and enjoying experimentation, rather than device engagement while driving. The interitem correlation was .614 and the Spearman–Brown coefficient was .761 (M = 3.10, SD = 0.79); no two-item exploratory factor analysis (EFA) or confirmatory factor analysis (CFA) was performed (Eisinga et al., 2013). The SAV value labels and thesis questionnaire materials indicate agreement anchors from 1 to 5. However, questionnaire-editor captures embedded in the thesis show frequency labels for the corresponding item content (Supplementary Information, Figure A1a–b and Table A13a). These captures document a conflicting questionnaire version, not the final participant-facing form; without the original platform export, the administered anchors remain unresolved. Table A1 records the scoring evidence. The source-keyed four-item reconstruction, mean(Q151, 6 − Q152, Q153, Q154), was retained only as a measurement sensitivity (Table A13).

Self-Reported Driving Behaviour

Three inherited sample-specific DBQ content scores were reconstructed from raw items. Mixed Errors and Violations, the empirical score originally called Errors and Violations in the thesis, averaged Q187–Q196, Q198, and Q201 (12 items; α = .948, ω = .954). Lapses averaged Q199 and Q202–Q204 (four items; α = .879, ω = .882). Aggressive Violations averaged Q179–Q181 (three items; α = .805, ω = .822). Higher means indicate more frequent endorsement of the relevant behaviour content. The SAV contains values from 1 to 5, although parts of the thesis present a 0–4 coding; the observed archive governs the descriptive results, and the discrepancy is retained in Supplementary Information, Table A1. These are

general-road self-reports, not commute-specific events or objective safety outcomes. The mean of all 19 final items was also calculated solely as a structural sensitivity outcome.

Covariates

Age was Q1, gender Q2, and driving experience in years Q5. Age and experience were centred at their analysis-sample means; in the N = 490 models, the male response category was coded 1 and the female category 0. These basic covariates were recorded in the parent study and retained across outcomes because age, gender, and accumulated driving experience may relate to exposure or self-reported road behaviour (Crundall and Underwood, 1998; Sheykhfard et al., 2022; Tao et al., 2017), not because they were significant in this archive. Exposure-covariate sensitivities are detailed in Supplementary Information, Table A8.

Measurement Considerations

The measurement audit reproduced the parent study's same-sample principal component analysis (PCA) with Varimax rotation and documented item deletion. For the 13 impulsivity items, KMO was .953 and Bartlett's $\chi^2(78) = 4238.40$, $p < .001$; the first component explained 58.81% of variance (Supplementary Information, Table A2). The final 19-item DBQ solution had KMO = .962 and Bartlett's $\chi^2(171) = 7221.01$, $p < .001$. The deletion sequence and three-component loadings are reported in Tables A3a and A3b. Horn parallel analysis nevertheless favoured one dominant DBQ component (Table A4a). Principal-axis extraction with oblimin rotation was an exploratory audit, with communalities accounting for factor correlations (Table A4b; Fabrigar et al., 1999; Horn, 1965; McNeish, 2018; Watkins, 2018). The outcomes are consequently treated as inherited sample-specific content scores, not independently confirmed dimensions. The overall 19-item mean assesses dependence on score partitioning rather than validating a latent structure (Tables A10a and A10b).

Statistical Analysis

The same hierarchy was applied to each primary outcome. Step 1 entered centred age, gender, and centred driving experience; Step 2 added centred impulsivity and PIIT; Step 3 added Impulsivity × PIIT. Ordinary least squares (OLS) provided point estimates, overall F tests, R^2, adjusted R^2, ΔR^2, and conventional F-change statistics. Coefficient inference used HC3 standard errors, t tests, and 95% confidence intervals to accommodate possible heteroscedasticity (Long and Ervin, 2000; White, 1980). HC3 addresses heteroscedasticity under independent observations; it does not correct possible dependence within work units. HC3 Wald tests evaluated the Step 2 two-predictor block and the Step 3 interaction. The three final impulsivity coefficients, three PIIT coefficients, and three interactions formed separate Holm families for three distinct inferential questions: adjusted impulsivity associations (RQ1), adjusted PIIT associations (ancillary), and moderation (RQ2) (Holm, 1979). Conventional F change describes incremental OLS fit; inference rests on HC3 estimates and the declared multiplicity adjustments. All inferential tests were two-sided. The nominal alpha level was .05, with Holm-adjusted

decisions applied to the prespecified coefficient families. Here, prespecified refers to the fixed secondary-analysis specification inherited before this rerun, not prospective preregistration.

An expanded transparency model entered Impulsivity × PIIT and the historically examined Driving Experience × PIIT term together. The six interaction estimates across three outcomes formed a family evaluated with Holm and Benjamini–Hochberg procedures (Benjamini and Hochberg, 1995). Conditional-slope interpretation required an interaction with an HC3 interval excluding zero, support after correction, and a consistent direction in key sensitivity analyses. No simple-slope or Johnson–Neyman figure was produced because the interactions did not meet this standard.

The fixed specifications inherited from the preceding analysis were recomputed from raw SAV items in Python on 9 October 2026, with a separate implementation checking the principal coefficients. These decisions preceded this rerun but followed knowledge of the parent findings; they were not prospective preregistration. Sample, scoring, quadratic-term, influence and exposure sensitivities retained the primary analysis as the reference. Logged or winsorised Q8/Q9 measures and the parent exposure-covariate specification are detailed in Supplementary Information, Table A8a; reconstructed-versus-saved scores and Spearman correlations appear in Tables A8b and A8c. Huber and median regression assessed distribution sensitivity, and robust Wald tests assessed predictor blocks (Tables A11a and A11b). Historical IBM SPSS records are distinguished from the current Python computation: SPSS was not rerun for this revision. Historical reconciliation and current software versions appear in Tables A14a and A14b, with runnable code supplied separately. The STROBE checklist in Supplementary Information identifies reporting locations and archive-related gaps (von Elm et al., 2007). Sample size was determined by the archive rather than a new prospective power calculation.

Use of generative AI

OpenAI Codex assisted with substantive drafting and organisation, statistical code development and checking, document preparation and language revision, using the study materials and author-provided directions. This assistance supported analysis verification and manuscript preparation, not data collection. Exact historical model/version identifiers were not retained. The human authors retain responsibility for independently verifying the data processing, references, interpretations and final text.

Results

Sample and Measurement

All 492 archived cases had complete focal items and covariates. The N = 490 primary sample followed solely from the HC3 estimability rule for the two singleton gender categories; both observations remained in the full-file sensitivity. Table 1 presents the sample disposition and participant characteristics. Ten respondents met at least two outcome-independent quality flags. Those flags are not invalid-response classifications, and the primary analysis retained the cases; definitions and overlap counts appear in Supplementary Information, Table A5.

The item audit reproduced the thesis-derived 13-item impulsivity score and the final 19-item three-component DBQ procedure. Parallel analysis nevertheless favoured one dominant DBQ component. The outcomes are therefore described as inherited, sample-specific content scores rather than independently confirmed latent dimensions. Item provenance, impulsivity statistics, the DBQ deletion sequence, and alternative factor results appear in Supplementary Information, Tables A1–A4. Supplementary Information, Table A10 reports the overall 19-item structural sensitivity, and Supplementary Information, Table A13 reports the intended four-item PIIT measurement sensitivity.

Descriptive Statistics and Correlations

Tables 2 and 3 present descriptive statistics, reliability, floor proportions, and Pearson correlations. Impulsivity correlated with Mixed Errors and Violations, r = .301, Lapses, r = .376, and Aggressive Violations, r = .277 (all p < .001). Its correlation with PIIT was effectively zero, r < .001, p = .997. PIIT was not significantly correlated with any driving score (rs = − .072 to .047). The driving scores were moderately to strongly intercorrelated (rs = .506–.694). Spearman correlations in Supplementary Information, Table A8c supported the same description of the impulsivity associations.

Table 2

Descriptive statistics, reliability, and floor proportions

Variable	Items	M	SD	Reliability	Floor
Impulsivity	13	2.32	0.66	α = .939	3.7%
PIIT	2	3.10	0.79	SB = .761	2.6%
Mixed E/V	12	1.46	0.63	α = .948	36.0%
Lapses	4	1.85	0.73	α = .879	26.6%
Aggressive V.	3	1.84	0.75	α = .805	22.2%

Note. N = 492. Mixed E/V = Mixed Errors and Violations; Aggressive V. = Aggressive Violations. Reliability is alpha except PIIT (Spearman–Brown). Floor is the percentage at the minimum possible score. M = mean; SD = standard deviation; PIIT = personal innovativeness in information technology.

Table 3

Pearson correlations among the focal scores

Variable	1	2	3	4	5
1. Impulsivity					
2. PIIT	.000				
3. Mixed E/V	.301***	.047			
4. Lapses	.376***	−.015	.694***		
5. Aggressive V.	.277***	−.072	.605***	.506***	

Note. N = 492. Variable numbering follows Table 2. Lower triangle only. *** p < .001. Exact values are retained in the analysis archive. PIIT = personal innovativeness in information technology; Mixed E/V = Mixed Errors and Violations; Aggressive V. = Aggressive Violations.

Floor endorsement was highest for Mixed Errors and Violations (36.0%), followed by Lapses (26.6%) and Aggressive Violations (22.2%). Heteroscedasticity was also evident in the regression diagnostics. HC3 inference and distribution-sensitive models are reported alongside conventional OLS model-fit statistics.

Primary Regression Models

Model fit is reported in Table 4, focal coefficients in Table 5, and complete final-step coefficients in Supplementary Information, Table A6. Adding impulsivity and PIIT at Step 2 increased R^2 by .077 for Mixed Errors and Violations, .137 for Lapses, and .068 for Aggressive Violations (conventional F-change ps < .001); Step 2 HC3 Wald tests were F(2, 484) = 11.76, 25.94, and 14.47, respectively (all raw ps < .001; Supplementary Information, Table A11). These block tests are supplementary to the coefficient-family inference. Final-model statistics were F(6, 483) = 13.53, R^2 = .144; F(6, 483) = 14.04, R^2 = .149; and F(6, 483) = 12.46, R^2 = .134, respectively (all conventional model ps < .001). The interaction step added ΔR^2 = .004, .001, and .004; conventional F-change ps ranged from .129 to .494. Exact incremental estimates are reported in Supplementary Information, Table A13e.

Table 4

Hierarchical OLS model-fit statistics

Outcome	Step	R^2	Adj. R^2	ΔR^2	Statistic	df	p
Mixed E/V	1	.064	.058	—	F = 11.02	3, 486	< .001
Mixed E/V	2	.140	.131	.077	F change = 21.53	2, 484	< .001
Mixed E/V	3	.144	.133	.004	F change = 2.10	1, 483	.148
Lapses	1	.011	.005	—	F = 1.81	3, 486	.145
Lapses	2	.148	.139	.137	F change = 38.81	2, 484	< .001
Lapses	3	.149	.138	.001	F change = 0.47	1, 483	.494
Aggressive V.	1	.062	.057	—	F = 10.77	3, 486	< .001
Aggressive V.	2	.130	.121	.068	F change = 18.78	2, 484	< .001
Aggressive V.	3	.134	.123	.004	F change = 2.31	1, 483	.129

Note. Mixed E/V = Mixed Errors and Violations; Aggressive V. = Aggressive Violations. N = 490. Step 1 entered centred age, gender, and centred driving experience; Step 2 added centred impulsivity and PIIT; Step 3 added Impulsivity × PIIT. OLS = ordinary least squares; PIIT = personal innovativeness in IT; HC3 = heteroscedasticity-consistent type 3. R^2, adjusted R^2, ΔR^2, and conventional F/F-change statistics describe model fit. Inferential claims rest on HC3 coefficient estimates and the declared Holm adjustments; conventional model-fit p values are not heteroscedasticity-robust. Overall final-model $F(6, 483)$ values were 13.53, 14.04, and 12.46, respectively (all $p < .001$).

Impulsivity showed positive adjusted associations with each outcome: B = 0.262 for Mixed Errors and Violations, 0.413 for Lapses, and 0.282 for Aggressive Violations. Corresponding standardised β values were .274, .372, and .247, and every Holm-adjusted p was below .001 (Table 5). Lapses had the descriptively largest standardised coefficient; no formal test compared coefficients across outcomes. PIIT did not show a familywise-supported adjusted association. Driving experience showed no consistent pattern across outcomes.

Table 5

Final focal coefficients and multiplicity-adjusted inference

Outcome / predictor	B	HC3 SE	β	t	95% CI	Raw p	Holm p
Mixed E/V / Impulsivity	.262	.054	.274	4.89	[.157, .368]	< .001	< .001
Mixed E/V / PIIT	.045	.040	.056	1.13	[− .033, .122]	.258	.743
Mixed E/V / Impulsivity × PIIT	.065	.073	.063	0.89	[− .078, .208]	.374	.995
Lapses / Impulsivity	.413	.058	.372	7.10	[.299, .528]	< .001	< .001
Lapses / PIIT	−.006	.047	−.007	−0.13	[− .099, .087]	.896	.896
Lapses / Impulsivity × PIIT	.035	.073	.030	0.48	[− .109, .179]	.629	.995
Aggressive V. / Impulsivity	.282	.061	.247	4.59	[.161, .402]	< .001	< .001
Aggressive V. / PIIT	−.062	.054	−.065	−1.16	[− .168, .043]	.248	.743
Aggressive V. / Impulsivity × PIIT	.082	.084	.066	0.97	[− .083, .246]	.332	.995

Note. N = 490; residual df = 483. Mixed E/V = Mixed Errors and Violations; Aggressive V. = Aggressive Violations. B and β are OLS point estimates; HC3 supplies SE, t, confidence intervals, and raw p. Holm values use unrounded p values within separate three-test families for impulsivity, PIIT, and Impulsivity × PIIT. The interaction-family adjusted ps are .995.

Interaction Robustness

Table 5 gives the complete primary interaction family. Impulsivity × PIIT was unsupported for Mixed Errors and Violations, B = 0.0649, HC3 SE = 0.0728, t = 0.89, 95% CI [− 0.0783, 0.2080], raw p = .374; Lapses, B = 0.0355, HC3 SE = 0.0733, t = 0.48, 95% CI [− 0.1086, 0.1795], raw p = .629; and Aggressive Violations, B = 0.0815, HC3 SE = 0.0839, t = 0.97, 95% CI [− 0.0833, 0.2463], raw p = .332. Holm adjustment from unrounded probabilities gave adjusted ps = .995. Each interval included zero, and no interaction met the declared rule for conditional-slope analysis. The four-item PIIT sensitivity is reported in Supplementary Information, Table A13.

The expanded six-interaction family is reported in Supplementary Information, Table A7. No term survived Holm or Benjamini–Hochberg correction. Driving Experience × PIIT for Aggressive Violations was the smallest raw result, B = − 0.0171, HC3 p = .010, but Holm p = .059 and BH p = .059. This nominal secondary estimate does not support an additional moderation claim.

For the overall 19-item score, the impulsivity coefficient was B = 0.2972, HC3 SE = 0.0515, 95% CI [0.1960, 0.3984], p < .001; the PIIT coefficient was B = 0.0171, p = .655; and Impulsivity × PIIT was B = 0.0613, p = .381 (Supplementary Information, Table A10).

Supplementary Information, Tables A12a–A12b align all six historical PIIT interactions with the current estimates. The parent analysis reported conventional unadjusted support for the impulsivity interactions with Mixed Errors and Violations and Aggressive Violations, but not Lapses. It also reported support for the driving-experience interactions with Mixed Errors and Violations and Aggressive Violations, with borderline evidence for Lapses. Those historical results are distinguished from the present HC3 and multiplicity-adjusted estimates.

Diagnostics

Sample, scoring, functional-form, influence, and exposure-covariate results appear in Supplementary Information, Table A8. Adding logged Q8 and Q9, adding winsorised Q8 and Q9, or using the parent-thesis exposure-covariate structure preserved the positive impulsivity estimates and left every Impulsivity × PIIT interval crossing zero. The strict subset contained 480 cases. Huber and median regressions also retained positive impulsivity coefficients across the three content scores and overall score, while all interaction intervals included zero (Supplementary Information, Table A11).

Supplementary Information, Table A9 reports the remaining diagnostics. Across primary models, maximum variance inflation factor (VIF) was 1.24, minimum tolerance .81, and the largest condition index 2.53. Residual-normality and heteroscedasticity tests were significant. The regression specification error test (RESET) suggested possible functional-form departure for Mixed Errors and Violations and Lapses, but quadratic and distribution-sensitive estimates did not alter the interaction conclusion. Influence flags were evaluated only in fixed sensitivities and never used to redefine the primary sample.

Discussion

Principal Findings

The thesis-derived impulsivity composite showed consistently positive adjusted associations with all three inherited driving-behaviour content scores. The available two-item PIIT-derived score did not provide reliable evidence that these associations varied across PIIT levels under HC3 inference and Holm correction (Table 5). The adjusted associations and the moderation conclusion were stable across the principal sensitivity specifications. These findings concern self-reported behavioural content, not objective driving outcomes or individual risk classification.

Behavioural-science interpretation

The positive impulsivity associations are consistent with prior Chinese and international studies of impulsivity-related traits and driving self-reports (Ge et al., 2020; Pearson et al., 2013). The standardised coefficient was descriptively largest for Lapses, but no formal cross-outcome test was conducted. Shared response tendencies may contribute because predictors and outcomes were collected on the same occasion; a single common-method diagnostic cannot remove those influences (Podsakoff et al., 2024). These estimates concern adjusted associations rather than causal consequences of impulsivity.

Construct specificity and interpretation

A general willingness to try technology describes adoption orientation, not engagement with a specific device or task (Agarwal and Prasad, 1998). The two retained PIIT items did not identify reliable differences in the adjusted impulsivity associations. This finding cautions against interpreting a broad orientation as a proxy for processes occurring within a driving episode. Limited item coverage and the conflicting anchor records also restrict the test's sensitivity and interpretation. The results do not establish equivalence, refute PIIT theory or demonstrate that digital behaviour is unimportant. Future conditional models need measures that correspond to the activities through which a proposed association could arise.

Future conditional models should directly measure technology identity, function, timing, initiation versus response, and actual engagement. Mostyn Sullivan et al. (2021) assessed phone involvement and driving-related phone use; Qu et al. (2020) examined WeChat use. Young et al. (2024) used trip diaries to study executive function and device engagement, Truelove et al. (2025) distinguished phone behaviours and dependence, and Zhang et al. (2023) compared active and responsive scenarios. Those studies identify concrete measures with which to evaluate conditional associations before attributing the same information to a general adoption orientation.

Relation to the parent analysis and robustness

Conventional, unadjusted analyses in the parent thesis supported a stronger moderation interpretation. The present analysis differs in sample specification, predictor and exposure structure, covariance estimation and multiplicity control; no single change can be isolated as the cause of the difference. All six historical PIIT interactions are reconciled in Supplementary Information, Tables A12a and A12b, keeping standardised β distinct from unstandardised B. The broader models, overall driving score and fixed sensitivity analyses did not materially change the present moderation conclusion. The poorly reliable four-item PIIT reconstruction is a measurement warning, not corroboration. These comparisons clarify how dependent an inference is on its specification, but remain analyses of the same data.

Practical Implications and Future Research

The findings do not justify assigning drivers to educational groups using the two-item PIIT score. Positive adjusted impulsivity associations identify a question for prospective research, not a validated screening tool or evidence of differential training benefit. Response pauses, delayed nonessential action, self-monitoring and scenario practice are candidate content for future evaluation, rather than

interventions tested here. Reviews of distracted-driving interventions and hazard-perception training can inform that work but do not establish efficacy in this sample (Nicolls et al., 2024; Prabhakharan et al., 2024).

Behaviour-specific research also motivates evaluating predeparture navigation settings, notification suppression and safe stopping before digital tasks (Qu et al., 2020; Young et al., 2024; Zhang et al., 2023). These behaviours were not measured or tested in the present study. Any evaluation should specify comparison conditions and behavioural outcomes. Education is only one level of prevention: vehicle interfaces, technology design, road environments, enforcement and organisational expectations also shape attention demands.

Limitations and Future Research

First, this post hoc analysis was not preregistered and used previously analysed thesis data with parent findings already known. It is not an independent replication. Familywise adjustment limits false-positive claims within the declared families, but cannot remove the selection inherent in revisiting an existing archive or eliminate uncertainty across the wider set of exploratory sensitivities. Prospective studies should preregister scoring, covariates, outcome families, and decision rules, then evaluate them in an independent sample.

Second, a single-occasion, cross-sectional self-report design cannot establish temporal ordering or exclude shared reporting processes. The DBQ items concern general road behaviour rather than particular commutes, and the archive contains no crash, injury, or objective driving records. Repeated trip diaries, naturalistic observations, and appropriately consented device records could distinguish reported tendencies from actual episodes and their timing. Research relating DBQ content to naturalistic data and examining discrepancies between reported and proxied behaviour illustrates why these measurements should remain distinct (Jiao et al., 2023; Useche et al., 2022).

Third, the impulsivity composite combines urgency-related content with restlessness or sensation-seeking material, while PIIT has only two retained items and unresolved response anchors. The four-item reconstruction was poorly reliable ($\alpha = .328$, $\omega = .560$), with a negative corrected item–total correlation for reverse-scored Q152. The DBQ content scores arose from same-sample PCA and deletion; parallel analysis favoured one dominant component. The overall-score sensitivity shows that the moderation conclusion is not specific to the three-score partition, but does not validate factor structure (Supplementary Information, Table A10). Future studies need locked response anchors, prespecified impulsivity facets, broader behaviour-specific technology measures, and independent confirmatory measurement.

Fourth, recruitment and exposure records limit generalisation and adjustment. The 176 excluded returns cannot be reconstructed, and the archive lacks work-unit lists, individual selection records, selection probabilities, weights, and cluster identifiers. Probability-based representativeness cannot be established, and possible within-work-unit dependence was not modelled. HC3 standard errors do not

address that dependence, so their precision may be overstated if meaningful clustering was present. Skewed Q8 and Q9 exposure measures and ambiguity in the unit for Q10 complicate exposure adjustment. The two singleton gender categories also prevented stable HC3 estimation with full indicator coding, although both cases remained in the full-file sensitivity. Future multisite studies should preserve screening and exposure records, ensure adequate representation across response categories, and retain cluster identifiers for appropriate analysis.

Conclusions

The thesis-derived impulsivity composite was positively associated with all three inherited self-reported driving-behaviour content scores after adjustment. The available two-item PIIT-derived score did not provide reliable evidence that these associations varied across PIIT levels. Future studies should use prospectively specified measures of behaviour-specific technology engagement and objective or repeated driving outcomes when evaluating conditional associations and preventive interventions. No intervention was implemented or evaluated in the present study.

Abbreviations

BH
Benjamini–Hochberg
CI
confidence interval
DBQ
Driver Behaviour Questionnaire
EFA
exploratory factor analysis
CFA
confirmatory factor analysis
HC3
heteroscedasticity-consistent covariance estimator type 3
IT
information technology
KMO
Kaiser–Meyer–Olkin
OLS
ordinary least squares
PCA
principal component analysis
PIIT
personal innovativeness in information technology
RESET

regression specification error test
STROBE
Strengthening the Reporting of Observational Studies in Epidemiology
VIF
variance inflation factor.

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

Ethical approval for this study was granted by the Human Research Ethics Committee of Universiti Sains Malaysia (Jawatankuasa Etika Penyelidikan Manusia Universiti Sains Malaysia, JEPeM-USM), under protocol code USM/JEPeM/PP/26040355. The approval was issued on 14 August 2023 and is valid from 14 August 2023 to 14 August 2028.

Informed consent

Electronic informed consent was obtained from all participants before questionnaire completion during the May–October 2024 survey. Participation was voluntary, and the analytic archive contained anonymous responses.

Consent for publication

Not applicable. Only aggregate findings are reported; there is no identifiable individual participant information, image or case description.

Supplementary information

Supplementary Information contains Tables A1–A14, Figure A1a–b documenting questionnaire-editor captures, supplementary methods, a bibliography and the STROBE cross-sectional reporting checklist. Reproducibility Code contains the analysis files. These materials accompany this article.

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Author Contribution

S.S. contributed to the conceptualization, methodology, investigation, data curation, formal analysis, and preparation of the original manuscript draft. J.W. contributed to supervision, validation, project administration, and review and editing of the manuscript. Both authors read and approved the final manuscript.

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Generative AI assistance is disclosed in Methods.

Data availability

No new participant data were collected. Participant-level responses are not publicly released because of privacy and institutional-access restrictions. Editors and peer reviewers should route requests for verification data through the editorial office to the corresponding author, Shengxiang Sun (shengxiangsun@student.usm.my), so that reviewer identities need not be disclosed to the authors. The requested material would comprise the de-identified focal item and covariate data, a data dictionary and the analysis code needed to reproduce the reported results, supplied through an editor-approved confidential transfer route if institutional authorisation permits. Authorisation for that review-access arrangement has not yet been documented; access is therefore not guaranteed by this statement. This restriction must be resolved with the institution and disclosed to the journal before submission. Item mappings, analysis specifications and aggregate results are supplied in the Supplementary Information, and the accompanying Reproducibility Code contains no participant-level records.

Code availability

The accompanying Reproducibility Code archive provides Python code, environment requirements and prepared IBM SPSS syntax. No participant-level data are included; execution requires an authorised local SAV copy. SPSS was not rerun for this revision.

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