

Article

Exploratory Factor Analysis of the Driving Risk Checklist-25 Among Community-Dwelling Older Adults: Extraction of a Three-Factor Structure Based on Parallel Analysis and Its Clinical Interpretation

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Abstract

Background: Driving risk in older adults is multifactorial, and comprehensive on-road assessment is not always feasible in community practice. Although the Driving Risk Checklist-25 (DRCL-25) is easy to administer, interpretation based solely on the total score may obscure the type of driving difficulty. **Objective:** This study aimed to clarify the latent structure of the DRCL-25 in community-dwelling older adults and to propose a clinically interpretable three-factor solution based on parallel analysis. **Methods:** A total of 591 community-dwelling older drivers (mean age 75.9 ± 5.5 years), recruited through community-based long-term care prevention health checkups in Akita Prefecture, completed the DRCL-25. Internal consistency was examined using Cronbach's alpha. The suitability of factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity. The number of factors was examined by parallel analysis (1000 random datasets). Factors were extracted from the Pearson correlation matrix by maximum likelihood (ML) estimation and rotated using varimax rotation; an oblique (Promax) rotation was conducted as a sensitivity analysis. Loadings of $|0.30|$ or greater were used to support interpretation. The three-factor model and the total-score model were compared with respect to their association with mild cognitive impairment (MCI) status, determined using the National Center for Geriatrics and Gerontology Functional Assessment Tool (NCGG-FAT). **Results:** Internal consistency was acceptable (Cronbach's alpha = 0.767), the KMO value was 0.808, and Bartlett's test was significant ($\chi^2(300) = 2249.1$, $p < 0.001$). A three-factor solution, supported by parallel analysis and interpretability, was interpreted as (1) driving burden in complex situations, (2) danger signs noticed by others, and (3) reduced attention and orientation, together explaining 21.2% of total item variance. Factor-specific reliability was acceptable for Factor 1 ($\alpha = 0.725$) but low for Factor 2 ($\alpha = 0.459$) and Factor 3 ($\alpha = 0.460$). Oblique rotation indicated moderate-to-high inter-factor correlations ($r = 0.56$ – 0.63). The three-factor model and the total-score model showed comparable association with MCI status (AUC = 0.571 for both; this was a descriptive comparison, and no formal statistical test of the AUC difference was performed). **Conclusions:** The DRCL-25 showed an interpretable, although moderately inter-correlated, three-factor structure. Given its modest explained variance, the low reliability of two of the three factors, and the absence of incremental predictive validity over the total score,



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this structure should be regarded as provisional and hypothesis-generating, providing a conceptual and communicative framework rather than a validated basis for clinical decision-making at this stage.

Keywords: older adults; driving; Driving Risk Checklist-25; exploratory factor analysis; parallel analysis; varimax rotation

1. Introduction

Traffic safety among older drivers is a global concern, and declining driving ability has been linked to cognitive impairment as well as age-related changes in physical and sensory function [1,2]. In particular, older adults with mild cognitive impairment (MCI) or dementia are at increased risk of poorer driving performance and unsafe driving behaviors [3].

On-road assessment and driving simulator evaluation are considered valid approaches for assessing driving ability; however, both require specialized personnel, equipment, and time, making universal implementation difficult in community practice [4]. Accordingly, there is a need for screening tools that are feasible for use in clinical and community settings.

Self-administered questionnaires and checklists can be completed quickly and are useful for capturing subjective driving difficulties and everyday driving experiences [5,6]. However, the validity of self-evaluation varies across individuals, and discrepancies between self-perception and actual driving performance may affect safety [5].

Against this background, Kodama et al. reported the Driving Risk Checklist-25 (DRCL-25), a 25-item self-report measure designed to capture driving difficulties and warning signs among community-dwelling older adults, and showed that driving risk was higher in those with MCI [7]. More recently, efforts to validate tools for stratifying risk among older drivers have continued, underscoring the need for practical scales that can support clinical judgment [4].

Although the DRCL-25 is suitable for community implementation because it can quickly capture everyday driving difficulties and warning signs, a total score alone may not adequately reflect the qualitative pattern of driving problems. For example, an older adult whose main difficulty is handling complex traffic situations may require different support from someone whose main problem is reduced attention or disorientation. Clarifying the scale structure may therefore facilitate interpretation of the results and help translate assessment findings into intervention planning.

It should be noted that the present sample is drawn from the same ongoing community-based cohort in Akita Prefecture as our previous report [7], and the two samples therefore overlap in part because the cohort has continued to enroll and re-assess participants over time. The two studies, however, address distinct questions. Our earlier report examined group differences in DRCL-25 scores between participants with and without MCI, using the checklist as a univariate outcome measure. The present study instead examines the internal latent structure of the 25-item instrument itself, asking whether the items decompose into interpretable subdomains—a structural-validity question with direct implications for how the checklist should be scored and interpreted (total score versus domain-specific scores), and one that was not addressed in the earlier publication.

Exploratory factor analysis (EFA) is a standard approach for identifying the latent structure of multi-item scales, and Horn's parallel analysis is regarded as a useful method for factor retention [8]. Horn argued that decisions regarding the number of factors should not rely solely on the eigenvalue-greater-than-one rule because eigenvalues can be inflated by sampling error; instead, observed eigenvalues should be compared with those generated

from random data under the same conditions [8]. Varimax rotation has also been widely used to simplify factor structure and improve interpretability by maximizing the variance of squared loadings within each factor [9]; we additionally examined an oblique (Promax) rotation as a sensitivity analysis, given the possibility that the latent domains of driving difficulty are correlated rather than independent (see Sections 2.3 and 3.3).

Driving in later life is closely tied to access to healthcare, shopping, and social participation, whereas driving cessation may be associated with depressive symptoms and restricted activity [10–12]. National transport-statistics-based analyses have similarly highlighted substantial heterogeneity in older drivers' mobility patterns and risk by sex [13]. Therefore, support for older drivers should be staged and individualized, balancing safety with continued participation in everyday life.

Clarifying the latent domains of the DRCL-25 is important if the checklist is to function not merely as a screening tool but also as an assessment linked to support planning. If item clusters can be meaningfully organized, feedback to older adults and their families may become more concrete, and interdisciplinary communication may be facilitated. In addition, using parallel analysis for factor retention may reduce overfactoring and support a more stable estimate of the latent structure [8,14,15].

The aim of this study was to clarify the latent structure of the DRCL-25 in community-dwelling older adults using EFA, to present a three-factor solution based on parallel analysis, to examine the robustness of this solution under an oblique rotation and its factor-specific reliability, to compare the three-factor model with the total-score model in their association with an external criterion (MCI status), and to propose clinical interpretations for the identified factors.

2. Materials and Methods

2.1. Study Design and Participants

This cross-sectional study included 591 community-dwelling older adults who continued to drive in their daily lives. Participants were recruited through community-based long-term care prevention health checkups (Kihon Checklist-based screenings) conducted in collaboration with municipalities in Akita Prefecture, rather than through open volunteer advertisements. Inclusion required possession of a valid driver's license and current/recent driving in daily life. Individuals with visual disease, neurological disorders, or severe cognitive impairment that would preclude independent participation were excluded. The mean age of the participants was 75.9 ± 5.5 years. Data were collected between 1 April 2022 and 31 October 2025. The study was approved by the Ethics Committee of Akita University Graduate School of Medicine (approval No. 273) and the Ethics Committee of Akita Prefectural Cardiovascular and Neurosurgical Center (approval No. 26-06).

Because this cohort was drawn from a preventive health-checkup population of community-dwelling older adults who were independently able to attend such checkups and who continued to drive, the sample likely skews toward relatively lower-risk, higher-functioning older drivers; we did not collect structured driving-frequency or annual-mileage data, and this is discussed as a limitation (Section 4).

2.2. Measure

Basic demographic information, including age, sex, and years of education, was collected. Driving risk was assessed using the DRCL-25. The DRCL-25 is a self-administered checklist reported by Kodama et al. that assesses perceived driving-related difficulties and changes in daily driving using 25 items [7]. The total score is calculated as the simple sum of endorsed items, with higher scores indicating a greater number of driving-related difficulties or risk signs. The checklist is not intended to test driving skill directly; rather, it

is designed to identify warning signs that may affect safe driving. Each item is answered in a binary format (applicable/not applicable), and the checklist can be completed within a few minutes. The items cover cognitive and behavioral risks relevant to driving, including checking behavior, judgment, vehicle handling, attention, and orientation. Example items include delayed braking, difficulty merging or changing lanes, difficulty making right turns at large intersections, forgetting where the car was parked, forgetting the intended destination while driving, sleep problems, and use of sleep medication (Supplementary Materials). There were no missing responses on any of the 25 DRCL-25 items among the 591 included records (0% item-level missingness). No imputation was required, and the EFA was conducted on listwise-complete item data.

Mild cognitive impairment (MCI) status, used in Section 3.4 as an external criterion, was determined using the National Center for Geriatrics and Gerontology Functional Assessment Tool (NCGG-FAT) [16], a computer-based neuropsychological battery that assesses memory, attention, executive function, and processing speed against age- and education-adjusted normative data. Consistent with modified Petersen criteria and with the classification approach used in our previous report on this cohort [7], participants were classified as having MCI if their performance was ≥ 1.5 SD below normative means in at least one cognitive domain, in the absence of a diagnosis of dementia or significant impairment in activities of daily living.

2.3. Statistical Analysis

Descriptive statistics for the total DRCL-25 score were presented as the mean, standard deviation (SD), median, interquartile range (IQR), minimum, and maximum values. Item-level endorsement rates were calculated as the percentage of participants answering “applicable” for each item. Internal consistency was evaluated using Cronbach’s alpha for the total scale and separately for each retained factor (using the items assigned to that factor at the $|0.30|$ loading threshold). The suitability of the data for EFA was examined using the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett’s test of sphericity. The number of factors was examined by parallel analysis based on 1000 simulated random datasets of the same sample size and item number, comparing observed eigenvalues with the mean and 95th-percentile eigenvalues of the random datasets; the full eigenvalue comparison is reported in Supplementary Table S3. A three-factor solution was retained on the basis of both this statistical evidence and interpretability. Factors were extracted from the Pearson correlation matrix of the standardized items using maximum likelihood estimation and rotated with varimax (orthogonal) rotation as the primary solution; an oblique Promax rotation was additionally conducted as a sensitivity analysis to examine inter-factor correlations, given that varimax assumes factor orthogonality. We also attempted to compute tetrachoric correlations among items, which are generally recommended for binary items with skewed endorsement rates; however, because several items had very low endorsement rates, the resulting tetrachoric correlation matrix was numerically unstable (non-positive-definite/Heywood cases) and could not be used for a reliable factor solution, and is therefore not reported in further detail (the resulting risk of biased loadings from extracting factors on Pearson correlations of binary items is discussed as a limitation in Sections 4.3 and 4.4). Factor naming and interpretation were based primarily on loadings of $|0.30|$ or greater from the varimax solution. Communalities and uniquenesses were calculated from the varimax solution, and variance explained by each factor (and cumulative variance explained) was calculated as the sum of squared loadings divided by the number of items. To compare the total-score model with the three-factor model with respect to external validity, we fitted separate logistic regression models predicting MCI status (present versus absent) from (a) the total DRCL-25 score and (b) the three factor sub-scores,

and compared the area under the receiver operating characteristic curve (AUC) and Akaike Information Criterion (AIC) of the two models; this AUC comparison was descriptive only, and no formal statistical test of the AUC difference was performed. Statistical analyses were conducted using Python 3.11.2 with pandas 2.2.3, NumPy 1.24.0, scikit-learn 1.4.2, and statsmodels (version 0.14.1). Parallel analysis and figure generation were performed using Matplotlib (version 3.8.2).

3. Results

3.1. Participant Characteristics and Internal Consistency

The analysis included 591 community-dwelling older adults. The mean age was 75.9 ± 5.5 years; 335 participants were women (56.6%) and 256 were men (43.4%). The mean number of years of education was 12.3 ± 2.3 (Table 1). The mean DRCL-25 total score was 3.74 ± 3.59 , the median was 3 (IQR 1–5), and the observed range was 0–20 (Table 2; Figure S1). The score distribution was right-skewed, with many participants clustered at lower scores and a smaller number showing substantially higher scores. The 90th and 95th percentiles were 8 and 11, respectively. Internal consistency was acceptable (Cronbach's $\alpha = 0.767$), suggesting that the 25 items captured a coherent construct related to driving difficulties and risk signs. Item-level endorsement rates ranged from 0.8% to 50.7% (Table 2), and there was no item-level missing data.

Table 1. Participant characteristics.

Characteristic	Value
Participants, <i>n</i>	591
Age, years	75.9 ± 5.5
Sex	Women, 335 (56.6%); Men, 256 (43.4%)
Years of education	12.3 ± 2.3

Table 2. Descriptive statistics for the DRCL-25 total score and item endorsement rates. (a) Total score. (b) Item-level endorsement rate (% answering “applicable”); all items had 0% missing data.

(a)					
<i>n</i>	Mean $\pm$ SD	Median (IQR)	Range	90th Percentile	95th Percentile
591	3.7 ± 3.5	3 (1–5)	0–20	8	11
(b)					
Item #	Item	Endorsement Rate			
1	Steering in parking lots, etc.	10.6%			
2	Braking timing has become slower than before	9.0%			
3	Relies on mirrors rather than direct visual checking when changing lanes/turning	15.5%			
4	More startling or near-miss moments while driving	26.5%			
5	Less concerned about dirt or scratches on the car	29.1%			
6	Drives much less often for enjoyment	50.7%			
7	Forgets where keys or driver's license were put	15.9%			
8	Finds merging onto highways/changing lanes difficult	33.1%			
9	Cannot remember where the car was parked in a large parking lot	23.3%			
10	Difficulty parking within the lines of home garage/parking space	16.9%			
11	Feels more fatigued after driving than before	26.4%			
12	No longer understands the meaning of familiar road signs	8.3%			
13	Uncomfortable making right turns at large intersections	14.0%			
14	Pedestrians/bicycles suddenly appear when turning, requiring abrupt braking	12.0%			
15	Tends to forget to use the turn signal	2.7%			

Table 2. Cont.

(b)		
Item #	Item	Endorsement Rate
16	Makes wrong turns even on familiar roads	5.1%
17	Bothered by talking with passengers while driving	11.7%
18	Forgets where one was going while driving	3.5%
19	Usual passenger says driving has become rougher	4.6%
20	Has pressed brake and accelerator pedals by mistake	4.1%
21	Has unintentionally driven the wrong way	1.0%
22	Started driving after forgetting a passenger or luggage	4.1%
23	Has felt faint or close to losing consciousness while driving	0.8%
24	Often cannot sleep well at night; sleep is shallow	28.9%
25	Takes sleep-inducing medication	16.6%

3.2. Suitability for Factor Analysis and Factor Retention

The KMO value was 0.808, indicating good sampling adequacy for factor analysis, and Bartlett's test of sphericity was significant ($\chi^2(300) = 2249.1, p < 0.001$). These findings supported the presence of sufficient inter-item correlations for latent structure analysis. Parallel analysis based on 1000 random datasets indicated that the observed eigenvalues for the third, fourth, and fifth factors (1.328, 1.284, and 1.245, respectively) were only marginally above the corresponding 95th-percentile eigenvalues from random data (1.323, 1.281, and 1.243, respectively), indicating a statistically borderline retention decision beyond the first two factors (the full comparison for Factors 1–8 is reported in Supplementary Table S3). A three-factor solution was therefore adopted on the combined basis of this evidence and interpretability (Figure 1), consistent with our a priori clinical rationale for three conceptually distinct domains of driving difficulty.

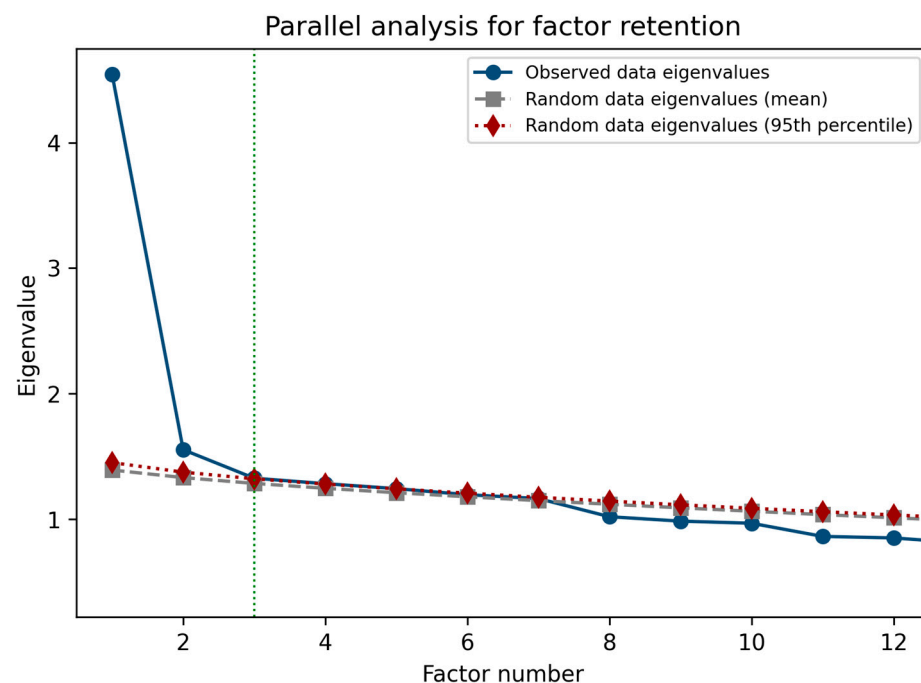


Figure 1. Parallel analysis for factor retention. X-axis: factor number (1–25). Y-axis: eigenvalue. Solid line: observed eigenvalues from the DRCL-25 correlation matrix. Dashed line: mean eigenvalues from 1000 random datasets of the same size. Dotted line: 95th-percentile eigenvalues from the random datasets. The vertical reference line marks the retained three-factor solution; eigenvalues for factors 3–5 were only marginally above the random-data 95th percentile.

3.3. Rotated Factor Solution and Clinical Interpretation

Based on the rotated factor pattern, the three factors were named and interpreted as follows. Representative items with relatively high factor loadings are shown in Table 3 (which also reports communalities and uniquenesses for all items), and the complete rotated loading matrix for all 25 items is provided in Supplementary Table S1. Together, the three factors accounted for 21.2% of the total item variance (Factor 1: 10.3%; Factor 2: 5.5%; Factor 3: 5.5%; cumulative 21.2%). This is a modest proportion: the three-factor solution leaves 78.8% of total item variance unexplained, and readers should weigh this explicitly when interpreting the factor structure (see Section 4.4).

Table 3. Representative items with higher factor loadings after varimax rotation.

Factor	Representative Item	Loading	Communality (h^2)
Factor 1: Driving burden in complex situations	Uncomfortable making right turns at large intersections (item 13)	0.59	0.381
Factor 1: Driving burden in complex situations	Steering in parking lots, etc. (item 1)	0.58	0.390
Factor 1: Driving burden in complex situations	Feels more fatigued after driving than before (item 11)	0.50	0.280
Factor 1: Driving burden in complex situations	Braking timing has become slower than before (item 2)	0.48	0.317
Factor 1: Driving burden in complex situations	Cannot remember where the car was parked in large parking lots (item 9)	0.41	0.220
Factor 2: Danger signs noticed by others	Usual passenger says driving has recently become rougher (item 19)	0.70	0.513
Factor 2: Danger signs noticed by others	Has unintentionally driven in the wrong direction (item 21)	0.49	0.246
Factor 3: Reduced attention and orientation	Forgets where one was going while driving (item 18)	0.71	0.528
Factor 3: Reduced attention and orientation	Makes wrong turns even on familiar roads (item 16)	0.35	0.201
Factor 3: Reduced attention and orientation	Has felt faint or close to losing consciousness while driving (item 23)	0.34	0.127
Factor 3: Reduced attention and orientation	Has pressed brake and accelerator pedals by mistake (item 20)	0.30	0.173

Factor 1, “driving burden in complex situations”, included items related to right turns at large intersections, steering operation in parking areas, delayed braking, loss of the parked car in large parking lots, and fatigue after driving. This factor appears to reflect higher cognitive-motor load in situations that require simultaneous judgment and vehicle handling. Cronbach’s alpha for the 13 items assigned to Factor 1 was 0.725 (Table 4).

Table 4. Internal consistency (Cronbach’s alpha) for the total scale and each retained factor.

Scale/Factor	No. of Items	Cronbach’s Alpha
Total DRCL-25 (25 items)	25	0.767
Factor 1: Driving burden in complex situations	13	0.725
Factor 2: Danger signs noticed by others	2	0.459
Factor 3: Reduced attention and orientation	4	0.460

Factor 2, “danger signs noticed by others”, included items such as being told by usual passengers that one’s driving had become rougher and having unintentionally

driven in the wrong direction. Although such events may be relatively infrequent, they represent warning signs of high safety relevance that are often recognized from an external perspective. This factor comprised only two items, and its internal consistency was low ($\alpha = 0.459$); we therefore interpret Factor 2 cautiously, as a content domain rather than as a presently reliable stand-alone subscale.

Factor 3, “reduced attention and orientation”, included forgetting the intended destination while driving, making wrong turns even on familiar roads, feeling faint while driving, and confusion between the brake and accelerator pedals. This factor may reflect instability in destination maintenance, route monitoring, and broader cognitive control during driving. This factor also comprised relatively few items (four), and its internal consistency was likewise low ($\alpha = 0.460$; Table 4); additional candidate items may be needed in future scale development to more fully capture this domain.

Six items (item 3: relies on mirrors rather than direct visual checking; item 5: less concerned about dirt/scratches on the car; item 7: forgets where keys/license were put; item 15: tends to forget the turn signal; item 22: forgot a passenger or luggage; item 25: takes sleep-inducing medication) did not reach the $|0.30|$ loading threshold on any of the three factors (Supplementary Table S1) and were not assigned to a factor; these items may capture more idiosyncratic or low-base-rate behaviors not well represented by the present three-factor structure.

Because varimax rotation assumes orthogonal (uncorrelated) factors, we additionally conducted an oblique Promax rotation as a sensitivity analysis. The Promax pattern matrix (Supplementary Table S2) identified essentially the same dominant items per factor as the varimax solution, supporting the substantive interpretation of the three domains. However, the corresponding inter-factor correlation matrix indicated moderate-to-high correlations among the three factors: $r = 0.629$ (Factor 1–Factor 2), $r = 0.562$ (Factor 1–Factor 3), and $r = 0.631$ (Factor 2–Factor 3) (Table 5). These correlations indicate that the three domains are related facets of a broader driving-risk construct rather than fully independent dimensions, and we retained varimax as the primary rotation for comparability with the item-loading interpretation above while explicitly noting this as a methodological limitation (Section 4).

Table 5. Inter-factor correlation matrix from the oblique (Promax) rotation.

	Factor 1	Factor 2	Factor 3
Factor 1	1.000	0.629	0.562
Factor 2	0.629	1.000	0.631
Factor 3	0.562	0.631	1.000

3.4. Comparison of the Total-Score Model and the Three-Factor Model

To examine whether the three-factor structure adds explanatory value beyond the total score, we compared logistic regression models predicting MCI status from (a) the total DRCL-25 score and (b) the three factor sub-scores, in the 589 participants with non-missing MCI and age data. The two models performed nearly identically (AUC = 0.571 for the total-score model and AUC = 0.571 for the three-factor model; AIC = 614.4 and 614.1, respectively; Table 6). This comparison is descriptive rather than based on a formal statistical test of the AUC difference; the near-identical AUC values (0.571 for both models) indicate no descriptively apparent advantage of the three-factor model over the total score, and this should not be read as a claim of statistical equivalence between the two models. The total score and Factor 1 sub-score were each weakly correlated with depressive symptoms (GDS-15 score; $r = 0.383$) and showed negligible correlation with age ($r = 0.087$ and 0.087 , respectively); Factor 2 and Factor 3 sub-scores showed weaker correlations with GDS-15 ($r = 0.099$ and $r = 0.172$, respectively) and with age ($r = 0.054$ and $r = 0.045$, respectively).

These results indicate that, with respect to the external criteria available in this dataset, the three-factor model did not outperform the total score, and we interpret the factor structure primarily as a tool for qualitative, domain-based interpretation rather than as a measure with demonstrated superior predictive validity (see Section 4).

Table 6. Comparison of the total-score model and the three-factor model in predicting MCI status ($n = 589$).

Model	Predictors	AUC	AIC
Total-score model	Total DRCL-25 score	0.571	614.4
Three-factor model	Factor 1, Factor 2, Factor 3 sub-scores	0.571	614.1

Note: AUC values are reported descriptively; no formal statistical test comparing the two correlated AUCs was performed.

4. Discussion

In this study, the DRCL-25 showed acceptable internal consistency and an interpretable three-factor structure derived from EFA with parallel analysis. Self-administered checklists are feasible for use in community settings because they impose less burden than on-road assessment or simulator testing; however, self-report may include both overestimation and underestimation of ability [5]. Rather than relying exclusively on the total score, it may be useful to also examine which domain of difficulty is predominant to help guide interviews, family input, and further evaluation when needed; however, our analysis comparing the total-score and three-factor models on an external criterion (MCI status; Section 3.4) found no evidence that the factor scores currently outperform the total score, and this qualification is carried through the remainder of the Discussion.

4.1. Theoretical and Practical Implications

Beyond its statistical properties, the proposed three-factor structure may offer conceptual value for understanding driving difficulties in older adults, even though—as detailed in Sections 4.3 and 4.4—these domains do not yet meet the threshold for independently validated subscales. Theoretically, distinguishing driving burden in complex situations (Factor 1) from danger signs noticed by others (Factor 2) and reduced attention and orientation (Factor 3) offers a more differentiated way of conceptualizing driving-related difficulty than a single undifferentiated total score. Factor 1 items cluster around situational and operational demand (e.g., turning, parking, timing of braking), Factor 2 items reflect externally observed behavioral change, and Factor 3 items reflect internally experienced attentional and orientational instability. This tripartite distinction may provide a more nuanced starting point for future construct development than the total score alone, even at this exploratory stage.

Practically, a domain-oriented reading of the DRCL-25 may support clinical assessment and communication in several ways, while stopping short of prescribing differential intervention pathways, which the present cross-sectional design cannot justify (Section 4.4). Identifying which domain is predominant for an individual respondent may help clinicians and occupational therapists structure follow-up conversations with older drivers and their families—for example, by prompting more specific questions about complex driving situations, by inviting family observations relevant to Factor 2 items, or by probing attentional and orientational experiences relevant to Factor 3—rather than relying on a single aggregate score that does not indicate which aspect of driving is most affected. This may make checklist feedback more concrete and easier to discuss in routine occupational therapy or driving-support consultations, even though, as demonstrated in Section 3.4, the current evidence does not show that factor scores predict mild cognitive impairment

status better than the total score, and the domains should not yet be used to allocate different interventions.

Looking forward, we propose a concrete validation pathway for this three-factor structure. First, additional candidate items should be developed and tested for Factors 2 and 3 to address their currently low internal consistency ($\alpha = 0.459$ and 0.460 , respectively). Second, the factor structure should be replicated in an independent sample not drawn from the partially overlapping cohort used here and in our earlier report [7]. Third, confirmatory factor analysis using estimators appropriate for binary items (e.g., WLSMV applied to polychoric correlations) should be used to formally test whether the proposed structure is sufficiently robust to support subscale development. Finally, the DRCL-25 and its factor structure should be evaluated against objective and prospective driving outcomes, including simulated or on-road driving performance, crashes, near-misses, and driving exposure, to establish whether domain-specific scores carry incremental predictive value beyond the total score.

4.2. Factor-Specific Interpretation

Factor 1, driving burden in complex situations, was characterized by items reflecting difficulties in environments with higher simultaneous processing demands, such as making right turns at large intersections, parking, adjusting braking timing, and experiencing fatigue after driving, and showed acceptable internal consistency ($\alpha = 0.725$). Previous studies have likewise shown that older adults and those with cognitive decline are more prone to driving errors when judgmental and operational demands increase [1,3,17]. For individuals scoring highly in this domain, possible avenues for future, prospective intervention research include avoiding complex intersections, structuring stepwise strategies for turning or parking, and reducing exposure to demanding conditions through route simplification, shorter trips, avoidance of rush hours, or accompaniment by a passenger; we emphasize that these remain hypotheses, as this cross-sectional, non-interventional study cannot establish that such strategies are effective or that this factor profile requires a distinct support pathway.

Factor 2, danger signs noticed by others, comprised items reflecting warnings identified by fellow passengers or major deviations such as wrong-way driving, but consisted of only two items and showed low internal consistency ($\alpha = 0.459$); we therefore interpret it as a content domain rather than a presently reliable subscale. In older adults with cognitive impairment, changes in driving behavior may be recognized earlier by family members or regular passengers than by the drivers themselves, and third-party observations may therefore contribute substantially to safer decision-making [1,18]. When this factor is elevated, it may be useful not only to provide feedback to the driver but also to systematically gather detailed examples from family members or passengers, such as episodes of near misses, hard braking, or lane deviation; whether this should prompt referral to specialized driving clinics is a question for future, prospective work rather than a conclusion supported by the present data. Discrepancies between self-report and passenger report may themselves represent meaningful risk information, but this was not directly examined here.

Factor 3, reduced attention and orientation, was primarily defined by items related to forgetting one's destination, making wrong turns on familiar roads, and other indicators of attentional or orientational instability, and also showed low internal consistency ($\alpha = 0.460$), likely reflecting the small number of items (four) currently assigned to this domain. Attention and orientation deficits in MCI and dementia have been associated with getting lost and with driving errors in previous work [3,10,18]. Possible support strategies for individuals with higher scores in this domain—such as restricting driving to daytime and familiar routes, simplifying trip plans, confirming destinations in advance, using navigation aids,

and early planning for alternative transportation—are presented here as hypotheses for future intervention research rather than established recommendations, consistent with the non-interventional design of this study. Despite their low internal consistency, however, it is clinically important to note that several items within Factors 2 and 3 describe behaviors that may be directly linked to serious traffic accidents: for example, unintentionally driving the wrong way (Factor 2, item 21), confusing the brake and accelerator pedals (Factor 3, item 20), and feeling faint or close to losing consciousness while driving (Factor 3, item 23). These are low-frequency but potentially catastrophic events. Even a single positive response to any of these items may warrant careful attention and further evaluation, irrespective of the factor subscale score or total score, and clinicians and family members should be alerted to their significance.

The goal of driving support for older adults is not only crash prevention, but also preservation of mobility and participation, and national transport-statistics-based analyses have highlighted substantial heterogeneity in older drivers' behavior and mobility needs; for example, an analysis of UK National Travel Survey data found marked differences in older drivers' driving patterns and risk by sex and age [13]. Reviews of interventions for older drivers suggest that educational approaches, cognitive and visual training, and transition support may have benefits, although effect sizes are often modest and multidimensional approaches remain necessary [11,12,19]. The three-factor structure identified here may eventually help translate checklist findings into tailored support strategies, including occupational therapy-based driving support, but, as noted above, this study—being cross-sectional and non-interventional—cannot demonstrate that individuals with different factor profiles actually require or benefit from different support pathways; we regard this as an important direction for future prospective and intervention research rather than a present conclusion.

4.3. Methodological Considerations

From a methodological perspective, the use of parallel analysis strengthened factor retention by reducing the risk of overfactoring compared with heuristic rules such as the eigenvalue-greater-than-one criterion [8,14,15]. Nevertheless, although varimax assumes orthogonal factors, our oblique (Promax) sensitivity analysis indicated moderate-to-high inter-factor correlations ($r = 0.56\text{--}0.63$; Table 5), suggesting that the three domains are correlated facets of a broader driving-risk construct rather than fully independent dimensions; this is an important limitation of the varimax-based interpretation presented as primary in this manuscript. We also attempted to compute tetrachoric correlations among the binary items, which are generally preferred for skewed binary data, but the resulting matrix was numerically unstable given the low endorsement rates of several items, and we were unable to obtain a reliable factor solution on this basis (Section 2.3). This is a substantive, not merely technical, limitation: extracting factors from Pearson correlations computed on binary items treated as continuous variables is known to risk attenuated or biased loadings and can generate spurious “difficulty factors” driven by similarity in item endorsement rates rather than by genuine content similarity. Because a stable tetrachoric-correlation alternative could not be obtained in the present sample, the possibility that some of the observed factor structure reflects endorsement-rate similarity rather than true latent content cannot be excluded, and the loadings and factor assignments reported here should be interpreted with corresponding caution. Future studies should examine structural validity more rigorously using confirmatory factor analysis with categorical-data estimators (e.g., WLSMV) and oblique rotation, ideally in larger or pooled samples that can support stable polychoric/tetrachoric correlation estimates.

4.4. Limitations

Several limitations should be noted. First, this was an exploratory analysis, and replication in independent samples (rather than the partially overlapping cohort used here and in our earlier report [7]) is needed. Second, the DRCL-25 is a self-report scale and may be influenced by response bias. Third, although we compared the total-score and three-factor models with respect to MCI status—descriptively, without a formal statistical test of the AUC difference—we did not examine associations with other external criteria such as passenger-based evaluation, crashes or traffic violations, near-miss events, or driving simulator outcomes, and the three-factor model did not show an advantage over the total score for the one criterion examined; convergent and predictive validity using a richer set of external, ideally prospective, driving outcomes remains an important direction for future work. Fourth, participants were recruited through community long-term care prevention health checkups and were, by inclusion criteria, current drivers with a valid license and without severe visual, neurological, or cognitive impairment; we did not collect driving-frequency or annual-mileage data, and the sample likely under-represents higher-risk or more impaired older drivers, limiting generalizability. Fifth, Factor 2 and Factor 3 showed low internal consistency ($\alpha = 0.459$ and 0.460 , respectively), and the present item pool may not be sufficient to support these as reliable stand-alone subscales without further item development. Sixth, the three factors together explained only 21.2% of total item variance, leaving most item-level variability unaccounted for by the retained structure; combined with the reliance on Pearson correlations for binary items (Section 4.3), this indicates that the present factor solution should be treated as preliminary. Taken together, these limitations mean that the three-factor structure is best regarded as provisional and hypothesis-generating rather than as a validated basis for clinical or community-based decision-making at this stage.

5. Conclusions

Among community-dwelling older adults, the DRCL-25 demonstrated a three-factor structure based on parallel analysis: (1) driving burden in complex situations, (2) danger signs noticed by others, and (3) reduced attention and orientation. However, these domains showed moderate-to-high intercorrelation under oblique rotation, together explained only 21.2% of total item variance, Factors 2 and 3 showed low internal consistency, and the three-factor model did not show a descriptively higher AUC than the total score in association with MCI status. Taken together, these findings indicate that the present three-factor structure should be regarded as provisional and hypothesis-generating rather than as a validated basis for clinical decision-making. At this stage, the domain structure is best used as a conceptual and communicative framework—for example, to help structure discussion of driving difficulties with older adults and their families (Section 4.1)—rather than as an independently validated set of subscales or as a tool shown to guide differential support planning. Further item development for Factors 2 and 3, independent replication, confirmatory modeling appropriate for binary items, and prospective validation against external driving outcomes (simulated or on-road performance, crashes, near-misses, and driving exposure) are needed before the three-factor structure can be recommended for clinical or community-based application.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/safety12050119/s1>. The full item list of the DRCL-25, the complete rotated (varimax) factor loading matrix (Table S1), the complete Promax pattern matrix (Table S2), the parallel-analysis eigenvalue comparison for Factors 1–8 (Table S3), and the distribution of the DRCL-25 total score (Figure S1) are provided as supplementary material.

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Abbreviations

AUC	Area under the curve
Bartlett's test	Bartlett's test of sphericity
CFA	Confirmatory factor analysis
DRCL-25	Driving Risk Checklist-25
EFA	Exploratory factor analysis
IQR	Interquartile range
KMO	Kaiser–Meyer–Olkin measure of sampling adequacy
MCI	Mild cognitive impairment
NCGG-FAT	National Center for Geriatrics and Gerontology Functional Assessment Tool
ROC	Receiver operating characteristic
SD	Standard deviation
Varimax	Varimax rotation
WLSMV	Weighted least squares with mean and variance adjustment

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