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**Cognitive screening for mild cognitive impairment: Clinician perspectives on
current practices and future directions**

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ABSTRACT

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26 This study surveyed 51 specialist clinicians for their views on existing cognitive screening
27 tests for mild cognitive impairment (MCI) and their opinions about a hypothetical remote
28 screener driven by artificial intelligence (AI). Responses revealed significant concerns
29 regarding the sensitivity, specificity, and time taken to administer current tests, along with
30 a general willingness to consider adopting telephone-based screening driven by AI.
31 Findings highlight the need to design screeners that address the challenges of
32 recognizing the earliest stages of cognitive decline and that prioritize not only accuracy
33 but also stakeholder input.

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36 **KEYWORDS:** Alzheimer's disease; mild cognitive impairment; mental status and
37 dementia test; artificial intelligence; attitude of health personnel

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INTRODUCTION

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43 Correctly recognizing the earliest stages of cognitive decline associated with Alzheimer's
44 disease [and related dementias](#) (ADRD) is crucial to maximize life quality and treatment
45 options and to reduce costs associated with disability and dependency [1,2]. However,
46 the identification of reliable signs of ADRD at the preclinical stage can be challenging,
47 especially for clinicians lacking specialist training [3,4], [with the result that many older](#)
48 [adults with memory concerns fail to receive an expert evaluation and diagnosis until the](#)
49 [disease has progressed markedly](#) [5,6]. A comprehensive cognitive evaluation typically
50 requires a lengthy in-person clinical examination by a psychologist or other trained
51 professional, which can be onerous in terms of access, time, and cost. Numerous brief
52 paper-and-pencil screening tests for dementia are available, [and typically are used in](#)
53 [healthcare settings](#) to identify people who would benefit from a full diagnostic workup [by](#)
54 [a specialist clinician](#) [7]. [These tests are also employed to identify participants for](#)
55 [inclusion in clinical trials](#) [8,9]. [However, cognitive screening tests](#) tend to vary in their
56 sensitivity to the earliest stages of decline [10] and are not universally offered in primary
57 care [settings](#) [11], [where concerned older adults typically first present](#) [5]. [Hence, new](#)
58 [methods for detecting early-stage cognitive decline are needed, and some of the most](#)
59 [promising capitalize on the rapidly advancing field of artificial intelligence \(AI\).](#)

60 **The Role of Artificial Intelligence in Cognitive Screening**

61 The development and application of AI-driven technologies in healthcare has grown
62 exponentially in recent years, and AI-driven tools to identify cognitive decline are being
63 applied across various modalities, including neuroimaging, genetics, blood biomarkers,

64 and speech and language [12-15], highlighting the potential for these methods to be used
65 in clinical settings for the detection of [early cognitive decline, also known as mild cognitive](#)
66 [impairment \(MCI\)](#). Many AI-based solutions offer clinical decision support to aid in
67 diagnosis, and tout benefits such as improved efficiency, accuracy, error detection, and
68 cost effectiveness. This, in turn, can lead to improved productivity and profit margins at
69 the organizational level [16].

70 Our own work utilizing AI to analyze speech recorded over the telephone has
71 demonstrated success in discriminating between cognitively healthy older adults, those
72 with MCI, and those with mild [Alzheimer's disease](#), is rated as enjoyable and engaging
73 by patients, and presents output to clinicians in a user-friendly dashboard interface
74 [13,17,18]. An additional benefit of this approach is that it can be administered remotely,
75 with the only technical requirement being that the patient have access to a telephone.
76 However, it is currently unknown whether AI-driven early detection tools will appreciably
77 improve patient outcomes [19].

78 Several studies have reported on physicians' attitudes towards AI in healthcare [20-23],
79 with those in favor citing benefits such as improved patient access to screening, improved
80 physician confidence in diagnosis, and reduced specialist time spent on tedious tasks
81 [22]. Despite this optimism, uptake has so far generally been low [24-27], with perceived
82 transparency and trustworthiness [emerging](#) as key concerns. [This may be due](#) to the
83 "black box" nature of AI, where the process underlying the system's operation and
84 [decision-making is unknown](#) [28]. Given the expected growth of AI-based clinical decision
85 support tools across almost all healthcare specialties, user feedback (including both
86 clinicians and patients) regarding acceptability will be crucial to ensure the technology's

87 adoption and realization of potential benefits. In addition to overcoming clinician
88 reluctance to adopt, any new AI-driven options for cognitive screening would presumably
89 need to demonstrate clear advantages over currently available paper-and-pencil
90 screeners. Two of the most widely-used cognitive screening tools are the Mini Mental
91 State Exam (MMSE [29]), and the Montreal Cognitive Assessment (MoCA [30]), both of
92 which are brief and easy to administer. However, previous reports of [both primary care](#)
93 [and specialist](#) clinician attitudes towards cognitive screeners cited several drawbacks,
94 including concerns about cost and time to complete testing, and a lack of specificity in
95 detecting MCI [6, 31, 32]. Hence, any new AI-based screeners would need to be as, or
96 more, accurate than current tools, cost effective, and brief.

97 With new AI-based screening approaches on the horizon, the opinions of specialist
98 clinicians regarding current screening practices are an important consideration for
99 potential uptake of these tools. The current study is novel in that it surveys a group of
100 clinicians specializing in dementia assessment for their views on currently available
101 cognitive screening tools, and their reactions to a hypothetical AI-driven screening service
102 delivered via the telephone. [Dementia specialists were selected under the assumption](#)
103 [that they have the most detailed knowledge and experience of cognitive decline and](#)
104 [would be in the best position to advise on how screening tests could be improved to](#)
105 [increase early detection.](#) Ultimately, specialist clinician-primary care provider
106 collaboration will be needed to evaluate new and evolving technologies in screening and
107 diagnosis to address the significant issue of underdiagnosis at the primary care level [33].

108 **MATERIALS AND METHODS**

Clinician views on cognitive screening

109 A 19-question survey was created [using Google Forms](#), with questions pertaining to the
110 professional settings of respondents, their opinions on current cognitive screening tools,
111 how they might be improved, and questions about uptake decisions for a hypothetical AI
112 telephone-based screening service (see Supplementary Material). [The survey questions](#)
113 [were developed by the first author based on a literature review of provider opinions about](#)
114 [cognitive screening. Two of the AI-specific questions were taken from a study examining](#)
115 [primary care provider opinions on uptake of a telephone screening service for cognitive](#)
116 [decline \[34\]. Responses to the AI-specific questions were measured on a 5-point likert-](#)
117 [type scale whereas the remaining questions required multiple choice or open-ended](#)
118 [responses.](#)

119 A convenience sample of clinicians specializing in dementia diagnosis were identified
120 [from two sources: the Alzheimer's Association and the American Association of Retired](#)
121 [Persons' Community Resource Finder](#) (<https://www.communityresourcefinder.org/>), [and](#)
122 [the Gerontological Society of America's GSA Connect](#) (<https://connect.geron.org/home>).

123 The survey link was emailed to [229](#) clinicians over a 9-month period in 2023 and posted
124 on *GSA Connect* in November 2023. [\(Email invitations had also been sent in 2020-2021](#)
125 [to 13 clinicians identified from the *Community Resource Finder*\).](#)

126 Fifty-two responses were [recorded \(response rate ~ 21.5%\)](#), although one was dropped
127 from analyses because the respondent indicated that they did not work in a clinical
128 capacity, resulting in a sample size of 51. Responses were anonymous, although
129 respondents were eligible to receive a \$10 Amazon gift card by providing their email
130 address, which was later deleted. This study was approved by the Marymount University

131 IRB #460. [Data analysis, including descriptive statistics and chi-square analyses were](#)
132 [conducted using SPSS version 27, with \$p < .05\$.](#)

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RESULTS

135 **Characterizing the sample**

136 As shown in Table 1, the majority of respondents had medical degrees and/or PhDs and
137 specialized in gerontology, (neuro)psychology, or neurology. Most respondents worked
138 in group settings of 20 or fewer colleagues, in university-affiliated medical centers. The
139 majority of respondents evaluated more than 10 older adult patients a week, with nearly
140 half spending more than 50% of their time conducting dementia evaluations.

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INSERT TABLE 1 HERE

142 **Opinions on current cognitive screeners for MCI**

143 The most notable concerns with current screening tools for MCI pertained to sensitivity
144 and specificity of the instruments (52.8%) and the time-consuming nature of testing
145 (32.2%) (see Figure 1). The most commonly cited suggestions for how this could be
146 improved were faster and/or shorter screening tests (24.2%) (see Figure 2).

147

INSERT FIGURES 1 & 2 HERE

148 **Opinions on an (hypothetical) AI-driven telephone screening service**

Clinician views on cognitive screening

149 The majority of respondents (78.4%) either agreed or strongly agreed that they would
150 make use of a telephone-based service that could identify MCI. A one-sample chi-square
151 goodness of fit test confirmed that the distribution of all the three types of responses
152 (agree, neutral, disagree) were significantly skewed towards positive opinions (chi-
153 sq=46.71, 2 df, $p<.001$). Opinions on whether *patients* would make use of a telephone
154 screener were less positively skewed (agree=50.0%; neutral=22%; disagree=28%), but
155 nonetheless still significant (chi-sq=6.52, 2 df, $p=.038$).

156 Cost was noted as a significant potential barrier to the implementation of a telephone
157 service to identify MCI, with over half (52.9%) of respondents stating that this would
158 influence their decision to adopt (chi-sq=10.71, 2 df, $p=.005$).

159 The most important characteristics of any proposed telephone service to screen for MCI
160 were identified by respondents as patient tolerability (92.2%), reliability (90.2%),
161 sensitivity (86.2%) and specificity (80.4%), with no significant differences in the
162 proportions of agree/neutral/disagree responses by characteristic (chi-sq=0.47, 3 df,
163 $p=.925$). Respondents provided a variety of preferred options when asked to name
164 standard screeners that would be useful to present side-by-side with speech-based data
165 for comparison purposes, citing the MoCa (38.6%) and MMSE (22.8%) most often. Other
166 preferred screeners noted were the Mini-Cog [35] at 14.9% and ADAS-Cog [36] (Conner
167 & Sabbagh, 2008) at 8.8%.

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DISCUSSION

170 Recent evidence suggests that MCI is woefully underdiagnosed in primary care settings
171 [33], arguing not only for improved education and training of primary care providers, but
172 also for the deployment of accurate, rapid, and well tolerated screening tools. The current
173 study surveyed clinicians specializing in the diagnosis of cognitive decline and dementia
174 for their opinions on the current state of cognitive screening for MCI, and they cited
175 several significant concerns. Consistent with previous reports, these concerns primarily
176 revolved around the lack of sensitivity and specificity of the tools and the time it takes to
177 administer, score and interpret them [31,32]. While commonly used tests like the MoCA
178 and MMSE are relatively brief, the time taken to administer and score them is not
179 inconsequential when medical appointments can be as short as 15 minutes [37].
180 Additionally, the MMSE's lack of sensitivity to the earliest stages of decline is well
181 documented [38,39], rendering it a poor choice for MCI detection. Several other options
182 are available, yet providers may be unsure of the "best" tests to use and when/how often
183 to use them (e.g., to avoid practice effects with repeated administration).

184 Respondents' most cited recommendation for the development of future cognitive
185 screeners was to ensure they be brief, presumably due to the time constraints noted
186 above [11,40]. The advantage of AI-based screeners, such as those using spoken
187 language, is that they can quantify cognitive decline using only short samples of speech
188 (in the 1-2 minute range). The AI computations themselves can occur almost
189 instantaneously, providing an output in real time. Our work, and that of others, has shown
190 that this approach can accurately differentiate MCI from both healthy aging and
191 Alzheimer's disease [13,17,41,42], is rapid, and well tolerated by patients [18]. Results of
192 the current study suggest that clinicians are also receptive to adopting an hypothetical AI

193 telephone-based screening service such as this, deeming sensitivity, specificity, reliability
194 and tolerability as especially important characteristics of any new tool. Our research in
195 developing a dashboard-type output to aid clinicians in the interpretation of an individual's
196 results suggests that both specialist clinicians and primary care providers alike could
197 adopt the technology with little additional training required [17]. The current findings
198 suggest that side-by-side comparisons with commonly used screeners such as the MoCA
199 and MMSE would be a valuable addition to this dashboard.

200 Several limitations should be noted in this study, with the potential for response bias being
201 the most important. A response rate of only 21.5% means that the majority of specialist
202 clinicians who were emailed the survey link did not respond, notably limiting the study's
203 external validity. While low, a response rate such as this is not uncommon from healthcare
204 providers [43,44] and several studies have proposed methods to increase survey
205 participation in this population [45,46]. A second limitation is that the questions regarding
206 the hypothetical AI-driven telephone screener were vaguely worded, such that
207 respondents may each have envisaged quite different versions of said tool, and this in
208 turn may have influenced results. For example, we never stated specifics such as whether
209 the service would be fully automated vs. having human interaction, which tasks would be
210 used to elicit speech samples, and how the speech samples would be recorded,
211 transmitted and analyzed. Whether and how any of these elements were considered by
212 respondents is unknown. Hence, a more detailed and realistic depiction of an AI
213 telephone screening tool will be an integral component of future work. Documented
214 clinician concerns over data privacy [22], coupled with the sheer number of AI-driven tools

Clinician views on cognitive screening

215 already available, most with limited transparency, means that patient autonomy and
216 privacy should be central ethical concerns for any clinician considering their use.

217 While respondents in the current study largely agreed that their older patients would use
218 a telephone-based screening service, there was a notable minority (28%) who did not
219 think that they would, for reasons we did not investigate. It is possible, at least in part,
220 that individual interpretations of what this “service” would entail resulted in a variety of
221 both positive and negative responses. The telephone is ubiquitous in most people’s
222 homes and allows for the remote administration of screening tests, but may not be
223 appropriate for patients with hearing, speech, or severe cognitive deficits. Tolerability of
224 fully automated tools may also be an issue for some older adults who would prefer the
225 opportunity to interact with a human [47].

226 Study limitations notwithstanding, these findings provide valuable insights on the current
227 state of cognitive screening for MCI from experts using these tools on a daily basis. The
228 proliferation of AI-driven healthcare technologies presents a great opportunity to address
229 the shortcomings of common cognitive screeners through the intelligent design of
230 accurate, brief and well tolerated tools in future.

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AUTHOR CONTRIBUTIONS

233 Catherine Diaz-Asper (Conceptualization; Methodology; Data Curation; Formal
234 Analysis; Investigation; Visualization; Funding Acquisition; Writing – Original Draft;
235 Writing - Review & Editing); Chelsea Chandler (Conceptualization; Writing - Review &
236 Editing); Brita Elvevåg (Conceptualization; Writing - Review & Editing).

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ACKNOWLEDGMENTS

239 The authors have no acknowledgments to report.

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FUNDING

242 This work was supported by a research grant to CDA from Rotary USA's Coins for
243 Alzheimer's Research Trust (CART) Fund.

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CONFLICT OF INTEREST

246 The authors have no conflict of interest to report.

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DATA AVAILABILITY

248 The data supporting the findings of this study are available on request from the
249 corresponding author. The data are not publicly available due to ethical restrictions.

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400

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402

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TABLES

404 Table 1. Characteristics of the study sample (N=51)

	N	%
Terminal degree		
MD	25	49.0
PhD	12	23.5
MD/PhD	2	3.9
DO	3	5.9
LCSW	2	3.9
Other (misc.)	7	13.7
Specialty		
Gerontology	18	35.3
Neurology	8	15.7
Internal Medicine	2	3.9
(Neuro)psychology	12	23.5
Psychiatry	4	7.8
Other (misc.)	6	11.8
Work setting		
Hospital (outpatient clinic)	8	15.7
University-affiliated medical center	31	60.8
Private office	12	23.5
Practice		
Group	38	74.5
Individual	13	25.5
Number of practice colleagues		
1-10	28	54.9
11-20	11	21.6
21-50	3	5.9
>50	3	5.9
unknown	6	11.8
Number of adult patients 65 or older seen per week:		
1-5	4	7.8
6-10	14	27.5
11-20	14	27.5
21-30	7	13.7
	10	19.6

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>30 unknown	2	3.9
Percentage of older adult patients presenting with memory concerns		
<10%	1	2.0
10-25%	9	17.6
26-50%	9	17.6
51-75%	12	23.5
>75%	20	39.2
Percentage of time spent on dementia evaluations		
<10%	6	11.8
10-25%	9	17.6
26-50%	13	25.5
51-75%	11	21.6
>75%	12	23.5

405

406

FIGURE LEGENDS

407 Figure 1. Percentage of total responses citing problems with current cognitive screeners
408 for the identification of MCI. (Respondents could indicate more than one option).

409 Figure 2. Percentage of total responses citing how current cognitive screeners for the
410 identification of MCI could be improved. (Respondents could indicate more than one
411 option).

412

413

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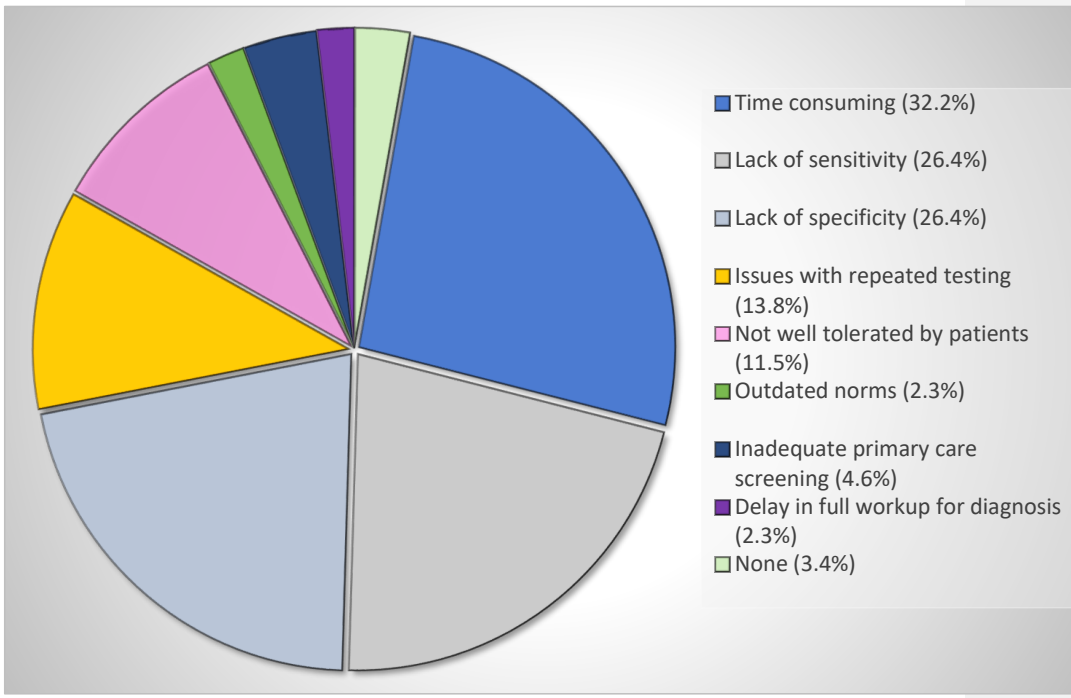
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FIGURES

417 Figure 1

418



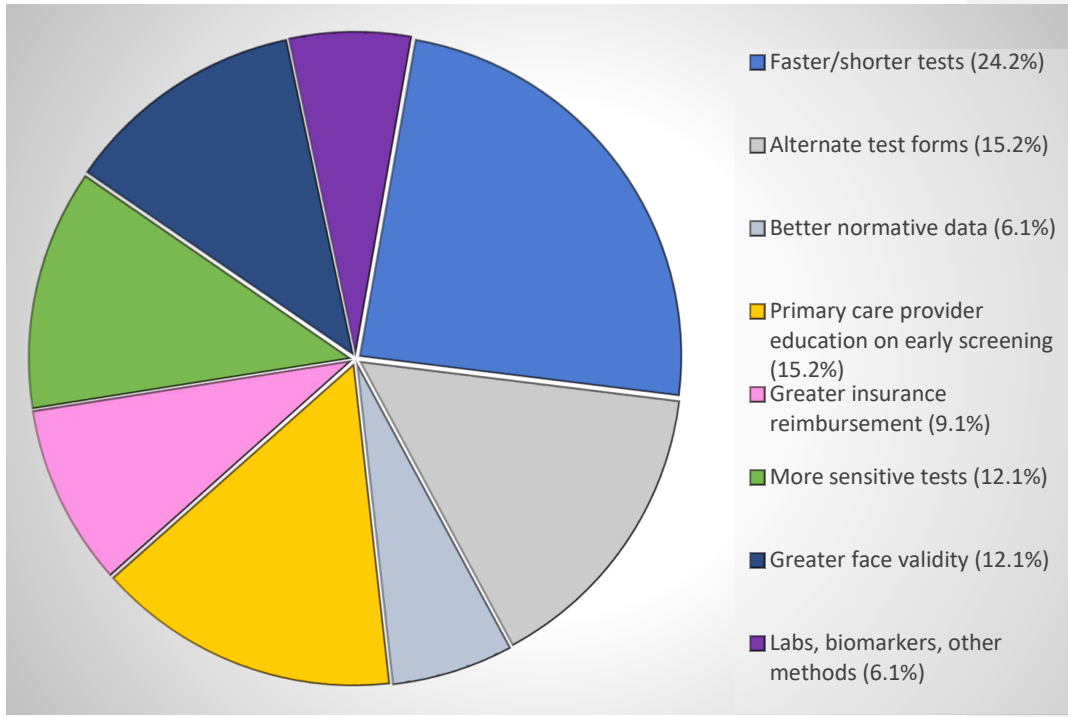
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421 Figure 2

422



423

424

425 **SUPPLEMENTARY MATERIAL**

426 **Clinician Survey Questions:**

427 Please provide us with some general information about yourself:

428

429 1. What terminal degree/qualification do you hold? (Select all that apply)

430 MD

431 DO

432 PhD

433 Other:

434

435 2. Which type(s) of specialty best describes you? (e.g., geriatrician, psychiatrist
436 etc.)

437

438 Please provide us with some general information about your practice setting:

439

440 1. What kind of setting best describes where you see patients (select all that apply):

441 Private Office

442 University-Affiliated Medical Center

443 Hospital

444 Other:

445

446 2. Do you work in an individual or group setting:

447 Individual

448 Group

449

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450 If you work in a group setting, how many colleagues work with you?

451

452 3. Approximately how many hours per week do you work in this setting?

453

454 4. Approximately how many older patients (> 65 years) do you see per week in this
455 setting?

456

457 5. Roughly, what percentage of your older patients present to you with memory
458 concerns?

459 Less than 10%

460 10-25%

461 25-50%

462 50-75%

463 More than 75%

464

465 6. Roughly, what percentage of your time is spent conducting dementia
466 evaluations?

467 Less than 10%

468 10-25%

469 25-50%

470 50-75%

471 More than 75%

472 7. In your opinion, what are some problems with the current state of assessment for
473 early cognitive decline/MCI? (select all that apply)

474 Lack of sensitivity

475 Lack of specificity

476 Issues with repeated testing

Clinician views on cognitive screening

- 477 Time consuming
- 478 Not well tolerated by patients
- 479 Other:
- 480

481 How could these be improved?

482
483 The following questions concern your opinion about whether you would (hypothetically)
484 be interested in a new telephone-based screening tool that could provide data about
485 early cognitive decline, without the need to see patients in person regularly:

486

487 1. If my practice was offered a service for patients over 65 years of age that could
488 identify MCI and early dementia, I would want to take advantage of it

489 strongly disagree

490 1

491 2

492 3

493 4

494 5

495 strongly agree

496 2. My patients would be likely to make use of a telephone service that could check
497 for signs of cognitive decline or dementia

498 strongly disagree

499 1

500 2

501 3

502 4

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503 5
504 strongly agree

505 3. How much would cost influence your decision to use a telephone service that
506 could identify MCI and early dementia?

507 Very much
508 1
509 2
510 3
511 4
512 5
513 Not at all

514 4. Please indicate how important the following factors would be in a telephone
515 service that could identify MCI and early dementia

516 Not at all
517 Somewhat
518 A lot
519 Very much
520

521 sensitivity (correctly identify MCI/early dementia)
522 specificity (correctly identify those without MCI/early dementia)
523 reliability (consistency)
524 tolerability for patients
525 sensitivity (correctly identify MCI/early dementia)
526 specificity (correctly identify those without MCI/early dementia)
527 reliability (consistency)
528 tolerability for patients
529

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530 5. If the service provided a dashboard interface with side-by-side comparisons
531 between the telephone- based data and existing screening tools, which would be the
532 most helpful to you? (select all that apply)

533 Mini-Mental State Examination (MMSE)

534 Montreal Cognitive Assessment (MoCA)

535 Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog)

536 Mini-Cog

537 General Practitioner assessment of Cognition (GPCOG)

538 Addenbrooke's cognitive examination (ACE-R or ACE-III)

539 Other:

540

541