

Asian Journal of Philosophy

Simion and Kelp on Trustworthy AI

--Manuscript Draft--

Manuscript Number:			
Full Title:	Simion and Kelp on Trustworthy AI		
Article Type:	Book Symposium		
Funding Information:	<table border="1" style="width: 100%;"> <tr> <td style="width: 60%;">Arts and Humanities Research Council (AH/W008424/1)</td> <td style="width: 40%;">Dr J Adam Carter</td> </tr> </table>	Arts and Humanities Research Council (AH/W008424/1)	Dr J Adam Carter
Arts and Humanities Research Council (AH/W008424/1)	Dr J Adam Carter		
Abstract:	<p>Simion and Kelp offer a prima facie very promising account of trustworthy AI. One benefit of the account is that it can straightforwardly explain trustworthiness in the case of cancer diagnostic AIs. What I query in this brief note is just how far beyond this specific case type – a case type which involves the acquisition by the AI of a representational etiological function – their account can be extended without overpredicting untrustworthiness.</p>		
Corresponding Author:	<p>J Adam Carter University of Glasgow Glasgow, Glasgow UNITED KINGDOM</p>		
Corresponding Author Secondary Information:			
Corresponding Author's Institution:	University of Glasgow		
Corresponding Author's Secondary Institution:			
First Author:	J Adam Carter		
First Author Secondary Information:			
Order of Authors:	J Adam Carter		
Order of Authors Secondary Information:			
Author Comments:	<p>The submitted critical piece is for the article symposium on *Trustworthy AI* by Mona Simion and Chris Kelp". There was no option under "book symposium" to click: *Article Symposium: Trustworthy AI*.</p>		

Simion and Kelp on Trustworthy AI

J Adam Carter
Reader in Philosophy
University of Glasgow
67-69 Oakfield Avenue
Glasgow, Scotland
United Kingdom

adam.carter@glasgow.ac.uk

Orcid ID: 0000-0002-1222-8331

Abstract:

Simion and Kelp offer a prima facie very promising account of trustworthy AI. One benefit of the account is that it can straightforwardly explain trustworthiness in the case of cancer diagnostic AIs. What I query in this brief note is just how far beyond this specific case type – a case type which involves the acquisition by the AI of a representational etiological function – their account can be extended without overpredicting untrustworthiness.

Keywords:

Trustworthy AI; trustworthiness; etiological functionalism; artificial intelligence

Data availability N/A

Code availability: N/A

Conflicts of interest: no conflict of interest to report.

Funding: Thanks to the AHRC *Digital Knowledge* (AH/W008424/1) project for supporting this work.

[Click here to view linked References](#)

Simion and Kelp on Trustworthy AI

Abstract

Simion and Kelp offer a prima facie very promising account of trustworthy AI. One benefit of the account is that it can straightforwardly explain trustworthiness in the case of cancer diagnostic AIs. What I query in this brief note is just how far beyond this specific case type – a case type which involves the acquisition by the AI of a representational etiological function – their account can be extended without overpredicting untrustworthiness.

1. Introduction

Increasingly, the question of whether – and if so under what conditions – artificial intelligence (AI) can be ‘trustworthy’ (as opposed to merely reliable or unreliable) is being debated by researchers across various disciplines with a stake in the matter, from computer science and medicine to psychology and politics.¹

Given that the nature and norms of trustworthiness itself have been of longstanding interest in philosophy², philosophers of trust are well situated to help make progress on this question. In their paper “Trustworthy Artificial Intelligence” (2023), Simion and Kelp (hereafter, S&K) aim to do just this.

I think they largely succeed. That said, in this short note I am going to quibble with a few details. In short, I worry that their reliance on function-generated obligations in their account of trustworthy AI helps their proposal get exactly the right result in certain central AI cases, such as cancer diagnostic AIs, but at the potential cost of overpredicting untrustworthiness across a range of other AIs.

¹ For some recent reviews, see, e.g., Kaur et al. (2022); and Kaur, Uslu, and Durresi (2020).

² See, e.g., Hardin (1996); Jones (2012); Frost-Arnold (2014); O’Neill (2018); Simion and Kelp (2022); Carter (2022). See also Carter and Simion (2020) for a review.

1 Here's the plan for the paper. In §2 I'll provide a brief overview
2 of S&K's account of trustworthy AI, emphasising the core
3 desiderata they take themselves to have met. In §3, I'll then raise
4 some potential worries, and discuss and critique some lines of
5 reply.
6
7

8 9 10 **2. S&K's line of argument**

11 A natural strategy for giving an account of trustworthy AI will be
12 a kind of 'application' strategy: (i) give a compelling account of
13 trustworthiness simpliciter and then (ii) apply it to AI, and make
14 explicit what follows, illuminating trustworthy AI in the process.
15
16

17 But, as S&K note, there is a problem that faces many extant
18 accounts of trustworthiness that might try to opt for that strategy.
19 The problem is this: many accounts of trustworthiness are such
20 that the psychological assumptions underlying them (e.g., that
21 being trustworthy involves something like a good will or virtue)
22 are simply too anthropocentric.
23
24
25
26

27 As S&K ask:
28
29

30
31 Do AIs have something that is recognizable as goodwill?
32 Can AIs host character virtues? Or, to put it more
33 precisely, is it correct to think that AI capacity for
34 trustworthiness co-varies with their capacity for hosting a
35 will or character virtues? (p. 4).
36
37
38

39 The situation seems to be this: an account of trustworthiness with
40 strongly anthropocentric psychological features 'baked in' will
41 either *not* be generalisable to AI (if AI lacks good will, virtue, etc.),
42 or it will be generalisable only by those willing to embrace further
43 strong positions about AI.
44
45

46 Ceteris paribus, a more 'generalisable' account of trustworthiness,
47 when it comes to an application to AI specifically, will be a less
48 anthropocentric one that could sidestep the above problem. One
49 candidate such account they identify is Hawley's (2019) negative
50 account of trustworthiness, on which trustworthiness is a matter
51 of avoiding unfulfilled commitments.³
52
53
54
55
56

57
58 ³ Another recent account of trustworthiness that is arguably not too
59 anthropocentric that it would be difficult to generalise over to AI is the
60 performance-theoretic account of trustworthiness. See here, Carter (2022).
61
62
63
64
65

1 S&K have argued elsewhere⁴ at length for a different -- and
2 similarly non overtly anthropocentric -- account of
3 trustworthiness, which they take to have advantages (I won't
4 summarise these here) over Hawley's: on S&K's preferred
5 account, trustworthiness is understood as a disposition to fulfil
6 one's *obligations*.
7

8
9 What is prima facie attractive about an obligation-centric account
10 of trustworthiness, for the purpose of generalising that account to
11 trustworthy AI, is that (i) artifacts can have functions; and (ii)
12 functions can generate obligations.
13
14

15
16 Let's look at the first point first. S&K distinguish between *design*
17 *functions* (d-functions), sourced in the designer's intentions, and
18 *etioloical functions* (e-functions), sourced in a history of success,
19 noting that artefacts can acquire both kinds of functions. S&K
20 use the example of a knife to capture this point:
21
22

23
24 My knife, for instance, has the design function to cut
25 because that was, plausibly, the intention of its designer.
26 At the same time, my knife also has an etioloical
27 function to cut: that is because tokens of its type have cut
28 in the past, which was beneficial to my ancestors, and
29 which contributes to the explanation of the continuous
30 existence of knives. When artefacts acquire etioloical
31 functions on top of their design functions, they thereby
32 acquire a new set of norms governing their functioning,
33 sourced in their etioloical functions. Design-wise, my
34 knife is properly functioning (henceforth properly d-
35 functioning) insofar as it's working in the way in which its
36 designer intended it to work. Etioloically, my knife is
37 properly functioning (henceforth properly e-functioning)
38 insofar as it works in a way that reliably leads to cutting in
39 normal conditions (p. 9).
40
41
42
43
44
45
46

47
48 While d-functions and e-functions (i.e., proper functioning) will
49 often line up, these functions can come apart (e.g., when artifacts
50 are designed to work in non-e-function-filling ways). When they
51 don't line up, S&K maintain that e-functions generally override.
52 As they put it:
53
54

55
56 what we usually see in cases of divergence is that norms
57 governing proper-functioning tend to be incorporated in
58
59

60 ⁴ See Kelp and Simion (2022).
61
62
63
64
65

1 design plans of future generations of tokens of the type: if
2 we discover that there are more reliable ways for the
3 artefact in question to fulfil its function, design will follow
4 suit (Ibid., p. 9).
5

6
7 So we have in view now S&K's thinking behind the idea that
8 artifacts (of which AI is an instance) can acquire functions. What
9 about the next component of the view: that functions can
10 generate obligations?
11

12
13 The crux of the idea is that a species of obligation, function-
14 generated obligation, is implicated by facts about what it is for
15 something to fulfil its e-function. The heart has a purely e-
16 function generated obligation to pump blood in normal
17 conditions (the conditions under which pumping blood
18 contributed to explanation of its continued existence). In
19 maintaining this, on S&K's line, we aren't doing anything
20 objectionably anthropocentric, any more than when we say a
21 heart *should* (qua heart) pump blood. We can easily extend this
22 kind of obligation talk over to artifacts, then: just as a heart is
23 malfunctioning (and so not meeting its e-functionally sourced
24 obligations) if it stops pumping blood, a diagnostic AI is
25 malfunctioning (and not meeting its e-functionally sourced
26 obligations) if it stops recognising simple tumours by their
27 appearance, and miscategorises them.
28
29
30
31
32
33
34

35
36 Against this background, then, S&K define an AI's being
37 *maximally* trustworthy at phi-ing as being a matter of having a
38 "maximally strong disposition to meet its functional norms-
39 sourced obligations to phi." The conditions for *outright* AI
40 trustworthiness attributions can then be characterised in terms of
41 maximal AI trustworthiness in the following way: an outright
42 attribution of trustworthiness to an AI is true in a context c iff
43 that AI approximates "maximal trustworthiness to phi"⁵ closely
44 enough to surpass a threshold on degrees of trustworthiness
45 determined by c, where the closer x approximates maximal
46 trustworthiness to phi, the higher x's degree of trustworthiness to
47 phi.
48
49
50
51
52

53 **3. Critical Discussion**

54
55
56
57

58
59 ⁵ A fuller exposition of the details of these ideas are spelled out in S&K work
60 on trustworthiness more generally, i.e., in Kelp and Simion (2022).
61
62
63
64
65

1 I suspect that a typical place one might begin to poke to look for
2 a hole in the above account would be the very idea that a machine
3 could have an obligation in the first place. Imagine this line or
4 reply: “But S&K have complained that extant accounts of
5 trustworthiness that rely on ‘virtue’ and ‘good will’ as
6 psychologically demanding prerequisites for being trustworthy are
7 too anthropocentric to be generalisable to AI. But isn’t being a
8 candidate for an ‘obligation’ equally psychologically demanding
9 and thereby anthropocentric? If so, haven’t they failed their own
10 generalisability desiderata by their own lights?”
11
12
13

14
15 The above might look superficially like the right way to press
16 S&K, but I think such a line would be uncharitable, so much so
17 that it’s not worth pursuing. First, we humans often have our own
18 obligations to others *sourced* in facts about ourselves (substantive
19 moral agreements we make, etc.) that are themselves predicated
20 on our having a kind of psychology that we’re not yet ready to
21 attribute to even our most impressive AI.
22
23
24

25
26 But S&K’s argument is compatible with all of this – viz., with
27 granting that obligations often times for creatures like us arise out
28 of features AI lack. What matters for their argument is just that
29 AI are candidates for e-function generated obligations, and it
30 looks like this is something we can deny only on pain of denying
31 either that AI can have e-functions, or that e-functions can
32 generate norms.⁶ I think we should simply grant both of these –
33 rather than incur what looks like an explanatory burden to deny
34 either.
35
36
37
38
39

40 The right place to press them, I think, is on the *scope* of the
41 generalisability of their account. Here it will be helpful to consider
42 again the case of a cancer-diagnostic AI which they use for
43 illustrative purposes. The etiological function that such cancer
44 diagnostic AIs acquire (which aligns with their d-function) is
45 going to be a purely *representational* function. Cancer diagnostic
46 algorithms are updated during the AI’s supervised learning
47 process (i.e., as is standard in deep learning) against the metric of
48 representational accuracy; the aim here is reliably *accurately*
49 identifying (and not misidentifying) e.g., tumours from images,
50 and thus to maximise representational accuracy via sensitivity and
51 specificity in its classifications. The AI becomes valuable to the
52
53
54
55
56
57
58

59 ⁶ For some representative defences of this idea, see, e.g., Graham (2014),
60 Simion (2019), Kelp (2018), Kelp and Simion (2021).
61
62
63
64
65

1 designer when and only when, and to the extent that, this is
2 achieved.

3
4 To use but one example, take the case of bladder cancer
5 diagnosis. It is difficult using standard human tools to reliably
6 predict the metastatic potential of disease from the appearance of
7 tumors. Digital pathology via deep learning AI is now more
8 reliable than humans at this task, and so can predict disease with
9 greater accuracy than through use of human tools alone (see
10 Harmon et al. 2020). This predictive accuracy explains the
11 continued use (and further accuracy-aimed calibration by the
12 designers) of such diagnostic AIs.
13
14
15
16

17 There are other non-diagnostic AIs with representational
18 functions as their e-functions. An example is FaceNet, which is
19 optimised for accuracy in identifying faces from images (Schroff,
20 Kalenichenko, and Philbin 2015; William et al. 2019).
21
22
23

24 AIs with purely representational e-functions, however, are –
25 perhaps not surprisingly – an outlier in AI more broadly. Let’s
26 begin here by considering just a few examples of the latest deep
27 learning AI from Google’s DeepMind. AlphaCode, for instance,
28 is optimised not for representational accuracy but for practically
29 useful coding. Supervised training, in this case, is not done against
30 a representational (mind-to-world) metric, but against a kind of
31 usefulness (world-to-mind) metric. In competitive coding
32 competitions, for instance, AlphaCode’s success (and what
33 explains its continued existence) is developing coding solutions to
34 practical coding problems and puzzles.
35
36
37
38
39
40

41 Perhaps even more ambitiously, the research team at DeepMind
42 is developing an AI optimised to ‘interact’ in human-like ways
43 three dimensional space in a simulated 3-D world (Abramson et
44 al. 2022). This AI is optimised in such a way that it will (given this
45 aim) acquire an e-function that is at most only partly
46 representational (e.g., reliably identifying certain kinds of
47 behaviour cues), while also partly practical (moving objects in the
48 3-D world).⁷
49
50
51
52

53 Next, and perhaps most notably, consider – in this case due to
54 the OpenAI research team – ChatGPT, a chatbot built on
55
56

57 ⁷ See, e.g.,
58 https://www.youtube.com/playlist?list=PLJ1sthn_UneUQ2avq5yCVszcbmc_mbege6
59
60
61
62
63
64
65

1 OpenAI's GPT-3 language models, and which provides 'human-
2 like' responses to a wide range of queries. Although ChatGPT is
3 often used for purposes of 'fact finding' (e.g., you can ask
4 ChatGPT to explain complex phenomena to you), it is not right
5 to say that this AI has a representational e-function. On the
6 contrary, ChatGPT is optimised for *conversational fluency*; to the
7 extent that accuracy misaligns with conversational fluency,
8 ChatGPT is optimised to favour the fluency metric.
9

10
11
12 Finally, consider a familiar AI – YouTube's recommender system
13 – which is optimised against the metric of (in short) 'keeping
14 people watching', and thus, generating advertising revenue
15 (Alfano et al. 2020). When the accuracy of a recommendation
16 choice (with respect to clustering towards videos of a similar
17 content-type which the user has watched) misaligns with a choice
18 more likely to keep the user watching more content, the algorithm
19 is optimised to recommend the latter. This feature of YouTube's
20 recommender system has been identified as playing a role in the
21 disproportional recommendation of conspiratorial content on
22 YouTube relative to viewers ex ante search queries.⁸
23
24
25
26
27

28
29 With the above short survey in mind, let's now return to the
30 matter of the *scope* of the generalisability of their S&K's account
31 of trustworthy AI. As I see it, at least, S&K's account can explain
32 trustworthy AI in cases where AI acquires representational e-
33 functions, such as the diagnostic AI example, and other AIs with
34 representational functions, like FaceNet. But – and here is where
35 I am less confident about their account – we've just seen that
36 many of the most touted and promising recent AIs either lack a
37 representational e-functions altogether (e.g., AlphaCode,
38 ChatGPT, etc.) *or* have such a function but only alongside other
39 practical e-functions (e.g., DeepMind's virtual world AI).
40
41
42
43
44

45 S&K seem to face a dilemma here. On the one hand, if e-function
46 generated obligations of the sort that a disposition to fulfil them
47 matters for AI trustworthiness are *not* limited to those obligations
48 generated by *representational* e-functions (but also include
49 obligations generated by *non-representational* e-functions), then it
50 looks like the view – problematically – predicts that YouTube's
51 recommender system, a known source of conspiratorial content,
52 is maximally trustworthy *so long as* it is maximally fulfilling all the
53 obligations generated by the e-function it has to 'keep viewers
54 watching' (in turn, maximising ad revenue profits). I take it that
55
56
57
58
59

60 ⁸ See Alfano et al. (2020).
61
62
63
64
65

1 this result is a non-starter. Which brings us to the more plausible
2 option and restrictive option: which is for a proponent of S&K's
3 view of trustworthy AI to hold that e-function generated
4 obligations of the sort that a disposition to fulfil them matters for
5 AI trustworthiness are limited to those obligations generated by
6 *representational* e-functions – such as, e.g., cancer diagnostic AIs,
7 FaceNet, etc.
8
9

10 Let's assume this later more restrictive route is taken. On this
11 assumption, we seem to get the result that, on S&K's view, all but
12 the minority of AIs being developed (those like cancer diagnostic
13 AIs, FaceNet, etc.) *fail* to meet the conditions for trustworthy AI.
14 So does this result *overpredict* untrustworthiness in AI? Here is one
15 reason for thinking that perhaps it does. Even if we grant that,
16 e.g., YouTube's recommender system (in virtue of its
17 documented propensity to recommend conspiratorial content, a
18 propensity that aligns with its fulfilling its practical e-function) is
19 an example of an 'untrustworthy AI' (and agree that S&K's view
20 predicts untrustworthiness correctly here), it's less clear that, e.g.,
21 AlphaCode should get classed together with YouTube's
22 recommender system. At least, it's not clear to me what resources
23 S&K's proposal have for distinguishing them given that neither
24 has been optimised to acquire a representational e-function.
25 Without some additional story here, then, the concern is that
26 S&K might overpredict untrustworthy AI even granting that the
27 view diagnoses some cases of untrustworthy AI (e.g., YouTube's
28 recommender system) as it should.
29
30
31
32
33
34
35
36
37
38
39

40 **4. Concluding remarks**

41
42 Giving a plausible account of trustworthy AI is no easy task; it is
43 no surprise that, at least in 2023, the themes of trustworthy and
44 responsible AI are among the most widely funded⁹ S&K's
45 account offers a welcome intervention in this debate because it
46 clarifies the kind of anthropocentric barrier to getting a plausible
47 account up and running from the very beginning, and it offers an
48 example of how such an account that avoids this problem might
49 go. My quibbles with the scope of the account in §3 remain, but
50 they should be understood as just that: quibbles that invite further
51
52
53
54
55

56 ⁹ Along with being a regular topic funded by academic funding agencies, the
57 importance of the question is also reflected in government-level funding. See,
58 e.g., this initiative by the UK government [https://apply-for-innovation-
59 funding.service.gov.uk/competition/1408/overview/e8b03fe9-ca18-415a-
60 852d-343f4231c442](https://apply-for-innovation-funding.service.gov.uk/competition/1408/overview/e8b03fe9-ca18-415a-852d-343f4231c442)
61
62
63
64
65

development of an account that is, on the whole, a promising
one.¹⁰

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

¹⁰ Acknowledgements [xxx].

References

- 1
2
3 Abramson, Josh, Arun Ahuja, Federico Carnevale, Petko
4 Georgiev, Alex Goldin, Alden Hung, Jessica Landon, et
5 al. 2022. 'Improving Multimodal Interactive Agents with
6 Reinforcement Learning from Human Feedback'. arXiv.
7 <https://doi.org/10.48550/arXiv.2211.11602>.
- 8
9 Alfano, Mark, Amir Ebrahimi Fard, J. Adam Carter, Peter
10 Clutton, and Colin Klein. 2020. 'Technologically
11 Scaffolded Atypical Cognition: The Case of YouTube's
12 Recommender System'. *Synthese*, 1–24.
- 13
14 Carter, J. Adam. 2022. 'Trust and Trustworthiness'. *Philosophy and
15 Phenomenological Research*.
- 16
17 Carter, J. Adam, and Mona Simion. 2020. 'The Ethics and
18 Epistemology of Trust'. *Internet Encyclopedia of Philosophy*.
- 19
20 Frost-Arnold, Karen. 2014. 'Trustworthiness and Truth: The
21 Epistemic Pitfalls of Internet Accountability'. *Episteme* 11
22 (1): 63–81. <https://doi.org/10.1017/epi.2013.43>.
- 23
24 Graham, Peter J. 2014. 'Functions, Warrant, History'. In
25 *Naturalizing Epistemic Virtue*, edited by Abrol Fairweather
26 and Owen Flanagan, 15–35. Cambridge University Press.
- 27
28 Hardin, Russell. 1996. 'Trustworthiness'. *Ethics* 107 (1): 26–42.
- 29
30 Harmon, Stephanie A., Thomas H. Sanford, G. Thomas Brown,
31 Chris Yang, Sherif Mehralivand, Joseph M. Jacob,
32 Vladimir A. Valera, et al. 2020. 'Multiresolution
33 Application of Artificial Intelligence in Digital Pathology
34 for Prediction of Positive Lymph Nodes From Primary
35 Tumors in Bladder Cancer'. *JCO Clinical Cancer Informatics*
36 4 (April): CCI.19.00155.
37 <https://doi.org/10.1200/CCI.19.00155>.
- 38
39 Hawley, Katherine. 2019. *How to Be Trustworthy*. Oxford University
40 Press, USA.
- 41
42 Jones, Karen. 2012. 'Trustworthiness'. *Ethics* 123 (1): 61–85.
43 <https://doi.org/10.1086/667838>.
- 44
45 Kaur, Davinder, Suleyman Uslu, and Arjan Durresi. 2020.
46 'Requirements for Trustworthy Artificial Intelligence—a
47 Review'. In *International Conference on Network-Based
48 Information Systems*, 105–15. Springer.
- 49
50 Kaur, Davinder, Suleyman Uslu, Kaley J. Rittichier, and Arjan
51 Durresi. 2022. 'Trustworthy Artificial Intelligence: A
52 Review'. *ACM Computing Surveys* 55 (2): 39:1-39:38.
53 <https://doi.org/10.1145/3491209>.
- 54
55 Kelp, Christoph. 2018. 'Assertion: A Function First Account'.
56 *Notus* 52 (2): 411–42.
- 57
58 Kelp, Christoph, and Mona Simion. 2021. *Sharing Knowledge: A
59 Functional Account of Assertion*. Cambridge University
60 Press.
- 61
62 ———. 2022. 'What Is Trustworthiness?' *Nous*.
- 63
64 O'Neill, Onora. 2018. 'Linking Trust to Trustworthiness'.
65 *International Journal of Philosophical Studies* 26 (2): 293–300.
<https://doi.org/10.1080/09672559.2018.1454637>.

- 1 Schroff, Florian, Dmitry Kalenichenko, and James Philbin. 2015.
2 'Facenet: A Unified Embedding for Face Recognition and
3 Clustering'. In *Proceedings of the IEEE Conference on Computer
4 Vision and Pattern Recognition*, 815–23.
5 Simion, Mona. 2019. 'Knowledge-First Functionalism'.
6 *Philosophical Issues* 29 (1): 254–67.
7 Simion, Mona, and Christoph Kelp. 2023. "Trustworthy Artificial
8 Intelligence". *Asian Journal of Philosophy*, no. Special
9 Inaugural Issue.
10 William, Ivan, Eko Hari Rachmawanto, Heru Agus Santoso, and
11 Christy Atika Sari. 2019. 'Face Recognition Using Facenet
12 (Survey, Performance Test, and Comparison)'. In *2019
13 Fourth International Conference on Informatics and Computing
14 (ICIC)*, 1–6. IEEE.
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65