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A literature review and research agenda

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Towards machine learning for moral choice analysis in health economics: A literature review and research agenda

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ABSTRACT

Background: Discrete choice models (DCMs) for moral choice analysis will likely lead to erroneous model outcomes and misguided policy recommendations, as only some characteristics of moral decision-making are considered. Machine learning (ML) is recently gaining interest in the field of discrete choice modelling. This paper explores the potential of combining DCMs and ML to study moral decision-making more accurately and better inform policy decisions in healthcare.
Methods: An interdisciplinary literature search across four databases – PubMed, Scopus, Web of Science, and Arxiv – was conducted to gather papers. Based on the Preferred Reporting Items for Systematic and Meta-analyses (PRISMA) guideline, studies were screened for eligibility on inclusion criteria and extracted attributes from eligible papers. Of the 6285 articles, we included 277 studies.
Results: DCMs have shortcomings in studying moral decision-making. Whilst the DCMs' mathematical elegance and behavioural appeal hold clear interpretations, the models do not account for the 'moral' cost and benefit in an individual's utility calculation. The literature showed that ML obtains higher predictive power, model flexibility, and ability to handle large and unstructured datasets. Combining the strengths of ML methods with DCMs has the potential for studying moral decision-making.
Conclusions: By providing a research agenda, this paper highlights that ML has clear potential to i) find and deepen the utility specification of DCMs, and ii) enrich the insights extracted from DCMs by considering the intrapersonal determinants of moral decision-making.

1. Introduction

Many (public) health decisions that policymakers make have a moral dimension. Think about policy issues where scarce resources must be allocated. Whom to provide treatment to during a public health crisis, a vaccinated or an unvaccinated patient? Should organ donation shortages be compensated with alternatives, such as xeno- or refurbished organ transplantations? Does society bear the financial burden of making orphan drugs available to save the lives of others in need? In such dilemmas, the moral dimension of decisions can be present explicitly – as in the framing of the decision contexts – while it can also be more implicit or latent (Forsyth and Nye, 1990; Schwartz, 1968; Greenwood, 2011). Whichever form they take, decisions that have a moral dimension can be categorised as either 'right' or 'wrong'. Moral decision-making is based on what those involved believe to be the right thing to do (Haidt, 2007). So, when facing moral dilemmas, stakeholder involvement and support (e.g., medical professionals, patients, and society) is important for policymakers to build effective and acceptable health policies.

Discrete choice models (DCMs), rooted in micro-econometrics and behavioural sciences, are widely advocated as a way to understand choice behaviours and inform health policy and clinical decisions (Soekhai et al., 2019). Based on the random utility theory (RUT), DCMs

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assume that a set of attributes can characterise choice alternatives and that a decision-maker's valuation (i.e., preference) depends upon the levels of these attributes (McFadden, 1981). The resulting choices reveal a latent utility function comprised of a systematic (observable) term containing the attributes in additive form and a random (unobservable) term capturing the unknown variation in decisions, where one chooses the alternative that maximises its utility (McFadden, 1974, 1981; de Bekker-Grob et al., 2012; Ben-Akiva and Lerman, 1985). Using DCMs allow thus investigation of the trade-offs between, e.g., cost and health outcome attributes characterising health interventions, services or policies from which economic insights can be extracted (Gadjradj et al., 2022; van den Broek-Altenburg and Atherly, 2020).

However, applying conventional linear-in-parameter DCMs in moral decision contexts is risky as moral decision-making is at odds with the models' assumptions (Chorus, 2015). Given the RUT, the models and their functional form do not consider the 'moral' costs and benefits. For instance, moral decision-making is often based on heuristics and emotions rather than utility-maximising principles (Gigerenzer, 2010; Haidt, 2001; Greene et al., 2001). Moreover, moral convictions and values affect decision-making when decision-makers face morally salient decisions; for example, an affective decision to provide one patient with care may reduce the overall (utilitarian) benefits but respect the patient's right to care (i.e., deontological considerations) (Haidt, 2007; Greene et al., 2004; Conway and Gawronski, 2013; Conway et al., 2018). Therefore, moral decision-making goes beyond the traditional functional form of the models, making it more complex than 'regular' decision-making. Ignoring the discrepancy between moral decision-making and the assumptions of the traditional DCMs could lead to erroneous model outcomes and misguided policy recommendations.

Recently, machine learning (ML) models have been extensively studied as a complementary modelling paradigm in the choice modelling field (Hillel et al., 2021; Van Cranenburgh et al., 2021). While DCMs contain functional forms and variable selection imposed by prior beliefs and behavioural theories, ML models learn patterns from the data more flexibly and accurately without *a priori* model assumptions, resulting in higher goodness-of-fit (Wang et al., 2021a). The models' flexibility can overcome problems of DCMs relating to the search for the optimal model specification and misleading insights caused by model misspecification (Rodrigues et al., 2019; Aboutaleb et al., 2020a, 2020b; Ortelli et al., 2021). Moreover, ML models work well with alternative types of data sources currently outside the realm of traditional DCMs (Bishop, 2006). Using alternative data sources, like text and image data, opens up the opportunity to enrich the analysis of moral decision-making rather than solely relying on explicit choice data.

Hence, combining DCMs and ML may help obtain accurate insights into moral decision-making and better inform policy decisions in healthcare and beyond when moral dilemmas occur. In this paper, our aim is twofold. Firstly, we aim to identify the characteristics of moral decision-making essential to discrete choice analysis approaches for studying moral decision-making in (public) healthcare settings. Secondly, we describe the strengths and weaknesses of using DCMs and ML for moral choice analysis based on the identified characteristics of moral decision-making. The latter results in a research agenda that lays out the directions for future research to bridge the gap between both paradigms.

2. Methods

We conducted a comprehensive review of studies focused on studies written in economics, machine learning, moral psychology, and empirical ethics. To capture all relevant studies, we generated two datasets. First, the core dataset was gathered by following a systematic search strategy. Second, the supplementary dataset enriched the systematic searches by screening reference lists from eligible studies in the core dataset. With the latter approach, we wanted to gather as many data points as possible to validate the findings from the systematic search strategy and ensure that state-of-the-art developments in the field are identified. Where applicable, our review study is reported according to the Preferred Reporting Items for Systematic and Meta-analyses (PRISMA) guideline (Moher et al., 2009). See Appendix A and Appendix B for the review protocol and PRISMA checklist, respectively.

2.1. Systematic search strategy

We used four databases to gather articles: PubMed, Scopus, Web of Science, and Arxiv. Where PubMed focuses on clinical and biomedical literature, Scopus and Web of Science include interdisciplinary studies. All three databases contain peer-reviewed articles. Arxiv is an open-source database aiming to disseminate papers not necessarily published in peer-reviewed outlets. It is, therefore, expected that trends at the intersection of computer science, statistics, and economics can be detected earlier compared to other reference databases.

Given the scope of this paper, we divided the search queries into five categories: (i) moral decision-making in healthcare, (ii) empirical ethics research regarding the distribution of scarce resources, (iii) moral dilemmas in policy analysis and economic evaluation, (iv) DCMs used for moral choice analysis, and (v) ML methods used for choice analysis in general. See Appendix C for a detailed overview of the search queries. All authors and an independent external researcher jointly defined the search queries.

The search queries were entered in the Advanced Search sections while specifying All Fields as the search domain. No restrictive Time Span was set, resulting in a Time Span between 1955 and 2021. Duplicates and articles without abstracts or identifiers (IDs) were removed, such as DOIs and Arxiv IDs. The searches were initiated and finalised in April 2021, after which the selection of articles and full-text screening was conducted.

An article was deemed eligible if it met the following three inclusion criteria. First, the article must have either empirically examined moral decision-making, focused on decision-making when encountering dilemmas in the distribution of (healthcare) resources, used DCMs to analyse moral decision-making or alternative decision rules, or used ML for discrete choice analysis in general. Second, the article had to be English-language articles. Finally, the article had to be available in full-text. Table 1 shows the criteria used to screen articles for eligibility. We conducted full-text screening when an article met the inclusion criteria. For all eligible articles, we used a set of attributes, shown in Table 2, to ensure consistency in data extraction. It should be noted that articles using DCMs were excluded when terms related to morality or (empirical) ethics were absent. In contrast, ML articles were not restricted to moral decision contexts. Given that ML recently gained the interest of the DCM community (Hillel et al., 2021; Van Cranenburgh et al., 2021), it is expected that no methodological advancements have been made to study moral decision-making.

After removing all duplicates and articles without abstracts or IDs, all authors conducted the selection of articles. Specifically, the first and last authors conducted the initial screening of all collected articles. When there were disagreements about the article's eligibility, the second and third author and an independent external researcher were consulted.

Table 1
Inclusion criteria to screen articles for eligibility.

Criteria	Inclusion criteria
Purpose of the study	Empirically examined moral decision-making OR focused on decision-making when encountering dilemmas in the distribution of (healthcare) resources OR used discrete choice models to analyse alternative decision rules OR used discrete choice models to analyse moral decision-making OR used machine learning for discrete choice analysis more generally
Written language	English-language text
Format of the study	Available in full-text

Table 2
Attributes for data extraction.

No.	Description
C1	**Research metadata**
C1a	Field of research
C1b	Year of publication
C1c	Type of study
C1d	Nature of dataset
C1e	Sample size
C1f	Type of study population
C2	**Moral decision-making in healthcare**
C2a	Decision context
C2b	Type of moral dimension
C2c	Emotion, heuristic, value and/or norm used in moral choice
C3	**Discrete choice modelling for moral choice analysis**
C3a	Type of discrete choice model
C3b	Model specification
C3c	Model validation (i.e., internal and external validity)
C4	**Machine learning methods for choice analysis**
C4a	Type of machine learning paradigm
C4b	Type of machine learning algorithm
C4c	Model specification
C4d	Model validation (i.e., internal and external validity)
C5	**Behavioural analysis and economic evaluation**
C5a	Types of extracted behavioural indicators
C5b	Type of economic appraisal

The same procedure holds for the full-text screening.

Based on the attributes shown in Table 2, the extracted data from the eligible articles were analysed in two ways. First, to create an overview of the variety of insights, the number of occurrences of each extracted attribute (as % of the relative number of studies in the respective category) was established. Second, the main conclusions related to attribute categories C2-5 in Table 2 of the eligible articles were analysed to obtain more in-depth insights. The first author extracted data. The remaining authors cross-checked the data extraction for articles focused on their expertise. Cross-checking was conducted for approximately ten percent of all articles subject to data extraction.

2.2. Scoping search strategy

The supplementary dataset was gathered to enrich the systematic (core) dataset. We used forward and backward searches on the reference list from eligible articles in the core dataset. The articles used for the scoping search strategy study how decision-makers *actually* make moral choices from a descriptive rather than a normative viewpoint. Moreover, we considered articles on the intersection of DCMs and ML, and ML in general, to identify trends that still need to be validated in the field of DCMs (e.g., research endeavours related to explainable artificial intelligence and causal inference). An article was deemed eligible based on at least fifty citation counts in the databases used for this study.

3. Results

The database searches identified 6285 articles, of which 6189 and 96 studies were part of the systematic and scoping searches, respectively. After excluding all duplicates and studies without abstracts or identifiers, we screened 4636 unique articles for eligibility. Two-hundred seventy-seven articles met the inclusion criteria and were subject to data extraction and analysis. Fig. 1 shows a PRISMA flowchart of the full study selection procedure.

The following subsections provide a description and a more in-depth analysis of the included articles. Table 3 shows a summary of the general characteristics of the included articles. For an overview of the extracted attributes per article, we would like to refer to Appendix D. The full dataset is available upon request.

3.1. The characteristics of moral decision-making

From all eligible articles that were subject to data extraction and analysis, 138 studies (50%) involve moral decision-making, either focused on health (Cookson, 2000; Brick et al., 2020; Arroyos-Calvera et al., 2019; Buckwalter et al., 2020; Preisz, 2019; Biddison et al., 2018; Laventhal et al., 2017; Minkoff et al., 2016; Bognar, 2015; Gillon, 2015; Caplan, 2014; Little et al., 2012; Kimmel et al., 2012; Bleichrodt and Pinto Prades, 2009; McKie et al., 2009; McKie and Richardson, 2017; Furnham and Ofstein, 1997; Furnham et al., 2002; Trnobranski, 1996; Myllykangas et al., 1996; Chant, 1989; Denburg et al., 2020; Ahlert and Schwettmann, 2017; Sheskin et al., 2016; Antiel et al., 2013; Fleck, 2011; Johri et al., 2009; Johri, 2003; Hurst et al., 2005; Fortes, 2002; Foster and McLellan, 1997; Faust and Menzel, 2011; Ottersen et al., 2008, 2014; Oliver, 2009; Green, 2009; Swenson, 1992; Pinho and Borges, 2015; Pinho and Pinto Borges, 2017; Churchill, 1983; Eyal et al., 2018; Justice, 2001; Pruski, 2018; Wilkinson et al., 2020; Krütli et al., 2016; Ubel and Loewenstein, 1996; Ubel, 1999; Irving et al., 2013; Stahl et al., 2008; Lerbæk et al., 2015; Arora et al., 2016; Varekamp et al., 1998; Oerlemans et al., 2015; Irvine and Donaldson, 1995; Rogge et al., 2016; Aggarwal et al., 2014; Ineichen et al., 2017; Englschalk et al., 2018; Hoffmaster, 2018; Marseille and Kahn, 2019; Cookson et al., 2018; Cookson and Dolan, 1999; Oberle and Hughes, 2001; van Delden, 2004; Ryynanen et al., 1996; Kilner, 1988; Nord et al., 1996; Nord, 1993; Bowling, 1996; Rogerson et al., 2011; Betan and Stanton, 1999; Giacomini et al., 2014; Garbutt and Davies, 2011; Huang et al., 2021; Musschenga, 2005; Tilburt, 2014) (55%) or general (Forsyth and Nye, 1990; Schwartz, 1968; Greenwood, 2011; Haidt, 2007; Gigerenzer, 2010; Haidt, 2001; Greene et al., 2001, 2004; Conway and Gawronski, 2013; Conway et al., 2018; MacAskill et al., 2020; sunstein cass r, 2005; Bourdieu, 2008; Jacobson and Timmons, 2012; Hooker and Luetge, 2013; Papaoikonomou et al., 2011; McAuliffe, 2019; Pölzler, 2015; Nyholm, 2015; Sauer, 2012; Bateman et al., 2002; Lin and Miller, 2021; Cosentino et al., 2020; Falk and Szech, 2013; Zhong et al., 2010; White, 2006; Patil et al., 2021; Kernohan, 2021; Hestermann et al., 2020; Zaleskiewicz et al., 2020; Roets and Bostyn, 2020; Bostyn and Roets, 2017; Crockett, 2016; Cummins and Cummins, 2012; Bénabou and Tirole, 2011; McClennen, 2010; Tinghög et al., 2016; Kumar, 2017; Engel et al., 2020; Lim, 2021; Royzman et al., 2011; Bauman et al., 2014; Bykvist, 2017; Grund et al., 2013; Harsanyi, 1975; Harsanyi, 1955; Huebner et al., 2009; Kahane, 2013; Kahane and Shackel, 2010; Kahneman and Frederick, 2005; Kahneman et al., 1991; Kahneman and Tversky, 1979; MacAskill and Ord, 2020; Rawls, 1974; Rawls, 1971; Thaler, 1988; Hertwig and Grüne-Yanoff, 2017; Lindbladh and Lyttkens, 2002; Payne et al., 1993; Schwartz, 2016; Harsanyi, 1976; Capraro and Perc, 2021) (45%) decisions. Almost all these articles examined moral decision-making from a personal (53%; e.g., Antiel et al., 2013; Haidt, 2001) or impersonal (46%; e.g., Denburg et al., 2020; Harsanyi, 1955) dimension. Only one article (1%; Greene et al., 2004) investigated both dimensions to study the difference between personal and impersonal moral decision-making.

Most of the 138 articles were empirical studies (62%; e.g., Fortes, 2002; Huang et al., 2021), followed by argumentative (33%; e.g., Fleck, 2011; Harsanyi, 1975), conceptual (3%; e.g., Schwartz, 2016; Kahneman et al., 1991), methodological (1%; e.g., Pruski, 2018) and literature review studies (1%; e.g., McAuliffe, 2019). When looking at the field of research, the number of articles was almost evenly distributed across three fields, namely economics (35%; e.g., Bleichrodt and Pinto Prades, 2009; Hertwig and Grüne-Yanoff, 2017), psychology (34%; e.g., Furnham et al., 2002; Gigerenzer, 2010) and philosophy (31%; e.g., Brick et al., 2020; Cookson, 2000).

3.1.1. Review of the literature

To explain the moral decision-making of individuals, 'economist-philosophers' like Harsanyi (1976) claim that decision-makers have two sets of preferences: i) personal preference based on self-interest and the

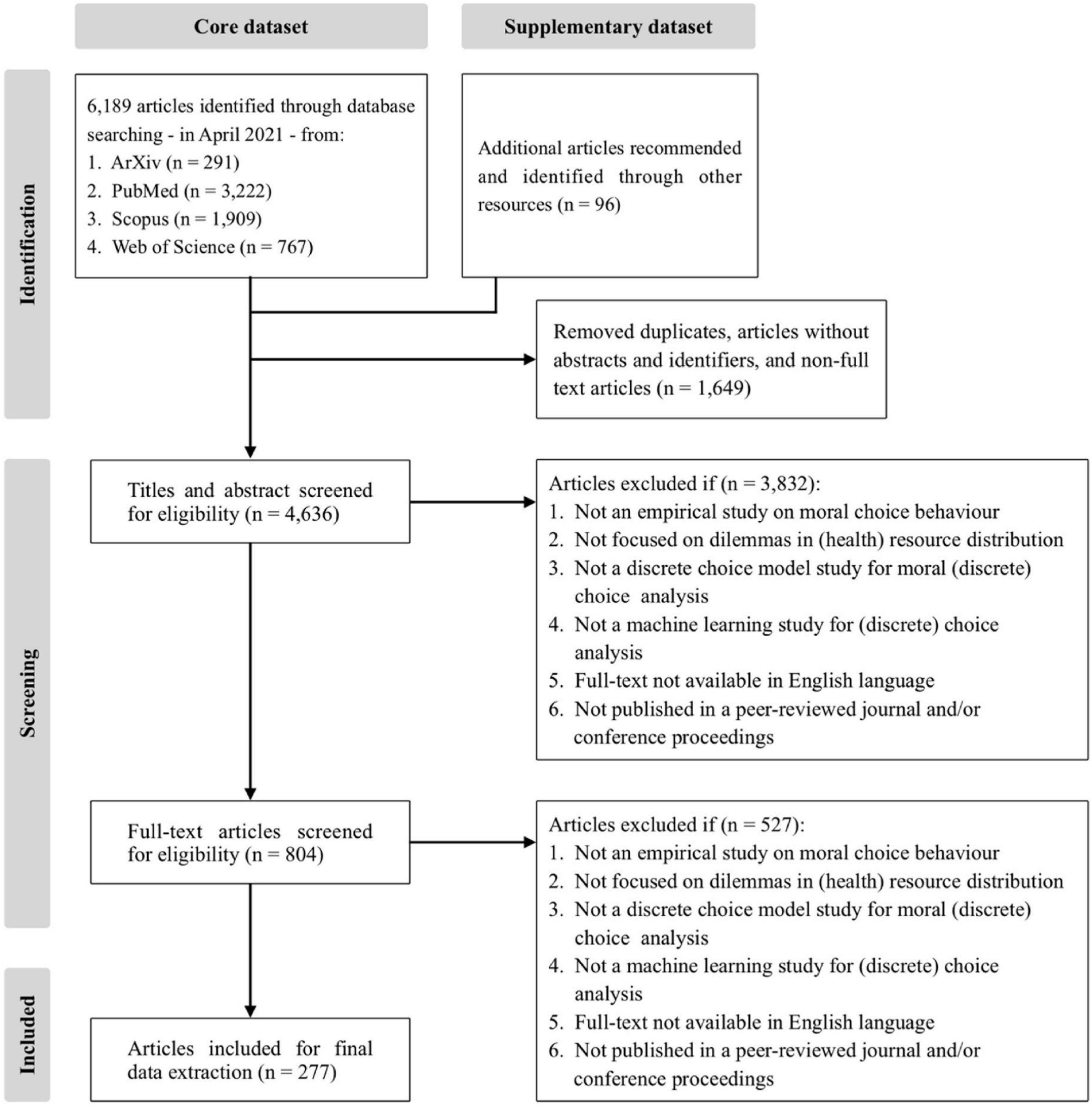

Fig. 1. PRISMA Flowchart for the study selection procedure.

interest of his close ones, and ii) moral preference. While some define moral preferences from a normative perspective (e.g., Harsanyi, 1976), others have taken a descriptive standpoint. Capraro and Perc (2021) proposed the moral preference hypothesis, according to which a decision-maker has preferences for following his norms – what he thinks to be the right thing to do – beyond the consequences that follow from the decisions for his utility. This does not mean that self-interest does not play any role in explaining moral decision-making, but simply that other psychological factors (e.g., moral motivation, perception, and attitude) should be considered (Conway et al., 2018; Faust and Menzel, 2011; Rogerson et al., 2011; Musschenga, 2005; Papaoikonomou et al., 2011; Cosentino et al., 2020; Roets and Bostyn, 2020; Bostyn and Roets, 2017; Crockett, 2016; Bénabou and Tirole, 2011; Tinghög et al., 2016; Schwartz, 2016). Other norms, such as injunctive (i.e., what others approve or disapprove) and descriptive norms (i.e., what others actually do in a given situation), can drive personal norms (Falk and Szech, 2013; Grund et al., 2013). These social norms can benefit a decision-maker's self-image by stimulating his self-worth and avoiding self-concept distress (Schwartz, 1968; Bourdieu, 2008; Hooker and Luetge, 2013; Lin and Miller, 2021; Zhong et al., 2010; Hestermann et al., 2020; Engel et al., 2020). Moral decisions are thus based on a decision-maker's norms to determine whether actions are 'good' and 'righteous', where different schools of moral thought can align with one's norms.

Another take on moral decision-making follows the work by Sunstein (2005) and Gigerenzer (2010), among other studies (Lim, 2021; Kahneman and Frederick, 2005; Kahneman et al., 1991; Kahneman and Tversky, 1979; Lindbladh and Lyttkens, 2002; Payne et al., 1993), who view decision-makers as being boundedly rational decision-makers. Instead of asking how moral decisions should be made, they examine how decision-makers actually make choices and argue that decision-makers use 'shortcuts' or heuristics (e.g., Punish betrayals of trust, Choose the default option, or Imitate your peers) when confronted with moral choice situations. Schwartz (1968) distinguishes moral choice situations from non-moral ones by suggesting two necessary conditions: i) one must be aware that his decisions are consequential and may affect the welfare of others and (ii) ascribe some responsibility for these acts and their consequences to himself. Consequently, a decision-maker must first perceive the choice situation as having a moral dimension before engaging in moral decision-making (Forsyth and Nye, 1990; Schwartz, 1968).

Table 3
Study characteristics (summary).

Item		N = 277[a]	%[b]
Topic area	Moral decision-making	138	(50)
	Discrete choice modelling for moral choice analysis	55	(20)
	Machine learning for discrete choice analysis	84	(30)
Main field of research	Economics	180	(65)
	Psychology	54	(19)
	Philosophy	43	(16)
Subfield of research	Health	95	(34)
	Transport	85	(31)
	General	83	(30)
	Marketing	9	(3)
	Environmental	5	(2)
Type of research	Empirical	122	(44)
	Methodological	83	(30)
	Argumentative	47	(17)
	Conceptual	14	(5)
	Literature reviews	11	(4)
Year of publication	2021	31	(11)
	2011–2020	148	(53)
	2001–2010	53	(19)
	1991–2000	23	(8)
	≤1990	22	(8)
Continent of origin	North America	71	(26)
	Europe	69	(25)
	Asia	12	(4)
	Oceania	12	(4)
	South America	5	(2)
	Africa	2	(1)
	Other	106	(38)

[a] Absolute number of articles.
[b] Relative number of articles (as % of 277 articles). Percentages may not add up to 100% because of rounding error.

Other studies focus on the underlying decision-making mechanisms. For instance, some studies (Preisz, 2019; Sheskin et al., 2016; Ineichen et al., 2017; Cummins and Cummins, 2012; Tinghög et al., 2016; Kumar, 2017) support the dual-process theory proposed by Greene et al. (2001) and claim that moral choices are either automatic (emotional and intuitive) or controlled (deliberative) processes. Greene et al., 2001, 2004 and other studies (Conway and Gawronski, 2013; Sheskin et al., 2016) have also found that automatic responses follow deontological judgments (whether the action is morally 'good'). In contrast, controlled reasoning tends to relate to utilitarian judgment (whether the outcome is morally 'righteous'). Another notion is the so-called 'post hoc rationalisation' (Greenwood, 2011; Jacobson and Timmons, 2012; Papaoikonomou et al., 2011; Nyholm, 2015). This concept relates to the 'social intuitionist' model proposed by Haidt, 2001, 2007. It assumes that moral decisions follow emotions and (social) intuitions, whereas deliberative reasoning occurs ex-post facto. Despite the large following among moral psychologists, severe doubts have been raised concerning the validity of the data obtained by a series of thought experiments (e.g., trolley-problems) (Bauman et al., 2014; Huebner et al., 2009; Kahane and Shackel, 2010).

3.1.2. Characteristics of moral decision-making for discrete choice analysis

As has become apparent in the previous subsection, many factors characterise moral decision-making. First, moral preferences follow (social) norms about what the decision-maker thinks to be the right thing to do. In contrast, the RUT underlying the traditional DCMs, assumes that all decisions are made based on strict self-interest and the interest of close ones (i.e., personal preferences) (McFadden, 1974, 1981; Harsanyi, 1976). Second, moral decision-making can be either controlled (deliberative) or automatic (emotional and intuitive), where deliberative reasoning occurs ex-post facto. Third, other psychological factors (e.g., moral motivation, perception, and attitude) affect moral decision-making. Simply assuming that decisions reflect one's preferences is insufficient to analyse moral decision-making with traditional DCMs. One's moral convictions are not captured by solely relying on the stated decisions, for which other psychological factors should be considered. Lastly, decision-makers can employ alternative decision strategies, ranging from boundedly rational rules, to fast and frugal heuristics, to rules based on emotions. As argued by, for example, Schwartz (1968) and Gigerenzer (2010), the frame of decisions determines which moral rule is employed in the decision-making.

3.2. Discrete choice models for moral choice analysis in (public) healthcare

Among all eligible articles, fifty-five articles (20%) used DCMs either in moral decision contexts (Chorus et al., 2018; Chorus et al., 2008; Skedgel et al., 2015; Skedgel and Regier, 2015; Oedingen et al., 2018; Chorus et al., 2021; Hancock et al., 2020a; Davison et al., 2010; Luyten et al., 2019; Luyten et al., 2015; O'Dell et al., 2019; Shiroiwa et al., 2016; Whitty et al., 2014a; Whitty et al., 2014b; Genie et al., 2020; Chorus et al., 2020; Shmueli et al., 2017; Haghani and Sarvi, 2019; Lu et al., 2021a; Reed et al., 2020; Shah et al., 2015) (39%) or incorporated different model specifications to account for alternative decision strategies (Abou-Zeid and Ben-Akiva, 2011; Cameron and DeShazo, 2010; Cantillo, 2005; Chorus and van Cranenburgh, 2014; Chorus, 2010; Fishburn, 1975; Fishburn, 1971; Gigerenzer and Selten, 2001; Gilbride and Allenby, 2004; Hensher et al., 2010; Hensher and Rose, 2012; Hess et al., 2013; Hess et al., 2012; Hole, 2011; Huber et al., 1982; Kivetz et al., 2004; Leong and Hensher, 2012; Louviere et al., 2008; Rooderkerk et al., 2011; Russo and Dosher, 1983; Scarpa et al., 2009; Simon, 1955; Simonson and Tversky, 1992; Swait and Marley, 2013; Swait, 2009; Swait and Adamowicz, 2001; Swait, 2001; Swait and Ben-Akiva, 1987; Tversky and Simonson, 1993; Tversky and Kahneman, 1991; Tversky, 1972; Tversky, 1969; Manski, 1977) (61%). Most articles analysed the decision-making of the general public (55%; e.g., Reed et al., 2020; Shah et al., 2015), followed by students (5%; e.g., Rooderkerk et al., 2011; Russo and Dosher, 1983), policymakers (2%; e.g., Shmueli et al., 2017) or patients (2%; e.g., Hole, 2011), or a mix of patients and health professionals (5%; e.g., Davison et al., 2010; ten Broeke et al., 2021). When looking at the decision context in which the studies were conducted, some articles focused on policy (27%; e.g., Luyten et al., 2015; Whitty et al., 2014a) and clinical (2%; e.g., Shah et al., 2015) decisions, whereas most articles developed DCMs for more general decision contexts (71%; e.g., Hess et al., 2012; Swait and Ben-Akiva, 1987).

In terms of the nature of the articles, most articles were empirical (36%; e.g., Skedgel et al., 2015; Chorus et al., 2020) or methodological (36%; e.g., Hancock et al., 2020a; Chorus et al., 2018), whereas the remaining articles were conceptual (18%; e.g., Swait and Ben-Akiva, 1987) or conduct literature reviews (10%; e.g., Chorus, 2015). Furthermore, most articles were conducted in the field of transport (35%; e.g., Chorus et al., 2008; Hensher et al., 2010), health (31%; e.g., Luyten et al., 2019; Lu et al., 2021a) or environmental economics (5%; e.g., Cameron and DeShazo, 2010), marketing sciences (5%; e.g., Kivetz et al., 2004), or economics more generally (24%; e.g., Huber et al., 1982). It should be noted that all non-health-related articles focused on incorporating alternative decision rules in the traditional DCMs.

3.2.1. Review of the literature

DCMs have established themselves as an important tool for analysing decision-making in health policy and clinical decisions (Soekhai et al., 2019). One of the discrete choice approaches used in the empirical health-related literature was discrete choice experiments (DCEs), which ask decision-makers to choose between two or more alternatives, characterised by attributes and differing in attribute levels, in a series of choice sets (Skedgel et al., 2015; Oedingen et al., 2018; Davison et al., 2010; Luyten et al., 2015, 2019; Shiroiwa et al., 2016; Genie et al., 2020;

Chorus et al., 2020; Shmueli et al., 2017; Lu et al., 2021a; Reed et al., 2020; Shah et al., 2015). Another approach used was profile case best-worst scaling (BWS), where decision-makers select their best and worst options among attributes and levels within choice sets (Whitty et al., 2014a). Both approaches can be categorised as stated preference (SP) methods where the data contains hypothetical choices between a set of alternatives (Ben-Akiva and Lerman, 1985). These methods combine high levels of experimental control and (statistical) efficiency to analyse trade-offs between multiple attributes.

Among the health-related SP studies, the moral dimension of decisions was present in a latent manner instead of explicit in the framing of the decision contexts. The combination of attributes used in the studies determined the moral dimension. For instance, Chorus et al. (2020) investigated whether one was willing to pay a higher one-off tax to decrease the number of deaths caused by the COVID-19 crisis as an artefact of the relaxation of the lockdown measures, among other health-related societal attributes. Reed et al. (2020) conducted a similar study, focusing on the extent one was willing to accept a greater spread of the COVID-19 virus to lift social-distancing restrictions and limit the economic impact of the pandemic. Additionally, two other studies (Lu et al., 2021a; Shah et al., 2015) focused on healthcare priority setting and the distribution of resources.

All health-related SP studies used a class of DCMs to estimate a decision-maker's utility function, where different models make different assumptions. One of the most used models in the literature was the multinomial logit (MNL) model (Skedgel et al., 2015; Oedingen et al., 2018; Davison et al., 2010; Luyten et al., 2019; Luyten et al., 2015; O'Dell et al., 2019; Shiroiwa et al., 2016; Whitty et al., 2014a; Genie et al., 2020; Chorus et al., 2020; Shmueli et al., 2017; Lu et al., 2021a; Shah et al., 2015). The MNL model assumes that preferences are homogenous across decision-makers, random errors are independent and identically distributed, and the independence of irrelevant alternatives (McFadden, 1974). Other models used were the mixed logit (MXL) (Luyten et al., 2019; Genie et al., 2020) and latent class logit (LCL) (Skedgel et al., 2015; Oedingen et al., 2018; Chorus et al., 2020; Reed et al., 2020) models, which both allow random variation relaxing the assumption of preference homogeneity.

The systematic component of the utility function imposes structure in the models, where its specification is guided by prior knowledge and behavioural assumptions (e.g., nonlinearities and employed decision rules). All health-related SP studies used the standard linear-in-parameter model specification with or without nonlinear effects. Only one article employed an alternative decision rule in the model; the so-called taboo trade-off aversion (TTOA) model (Chorus et al., 2020). The TTOA model was proposed by Chorus et al. (2018), who suggests that some trade-offs are morally problematic or taboo. The discrete choice modelling community has put much effort into developing various alternative decision rules or so-called semi- and non-compensatory specifications to improve the behavioural realism of the models (Abou-Zeid and Ben-Akiva, 2011; Cameron and DeShazo, 2010; Cantillo, 2005; Chorus and van Cranenburgh, 2014; Chorus, 2010; Fishburn, 1975; Fishburn, 1971; Gigerenzer and Selten, 2001; Gilbride and Allenby, 2004; Hensher et al., 2010; Hensher and Rose, 2012; Hess et al., 2013; Hess et al., 2012; Hole, 2011; Huber et al., 1982; Kivetz et al., 2004; Leong and Hensher, 2012; Louviere et al., 2008; Rooderkerk et al., 2011; Russo and Dosher, 1983; Scarpa et al., 2009; Simon, 1955; Simonson and Tversky, 1992; Swait and Marley, 2013; Swait, 2009; Swait and Adamowicz, 2001; Swait, 2001; Swait and Ben-Akiva, 1987; Tversky and Simonson, 1993; Tversky and Kahneman, 1991; Tversky, 1972; Tversky, 1969; Manski, 1977). See Leong and Hensher (2012) for a detailed review. Besides the TTOA model, morality in decision-making is rarely considered in this stream of literature (Chorus et al., 2018, 2020; Hancock et al., 2020a; Liebe and Meyerhoff, 2021).

The parameters of DCMs carry clear subject-matter interpretations. Because the attributes of the choice alternatives parameterise the models, the 'direct' utility valuations can be extracted. The literature shows that utility weights are estimated within the quality-adjusted life-year (QALY) framework, which measures the value of health outcomes (Skedgel et al., 2015; Shiroiwa et al., 2016; Shah et al., 2015), or to assess trade-offs between (public) health outcomes and equity considerations (Genie et al., 2020; Chorus et al., 2020; Shmueli et al., 2017). The 'indirect' utilities can also be derived to examine marginal valuations. Some studies derived the willingness-to-pay (WTP) and willingness-to-sacrifice (WTS) estimates (Chorus et al., 2020; Reed et al., 2020).

3.2.2. Strengths and weaknesses of discrete choice models

The conventional discrete choice approach has some strengths, making it a useful empirical tool for studying moral decision-making. First, as shown in the previous subsection, the specifications of DCMs are driven by *a priori* choice theoretical assumptions and domain knowledge to obtain the behavioural soundness in the models. Several alternative decision rules exist, such as the taboo trade-off aversion (Chorus et al., 2018, 2020) and random regret minimisation (Chorus, 2010), that can be employed in the models. Second, the models' mathematical elegance and behavioural appeal ensure that clear subject-matter interpretations can be extracted. For instance, actual attribute trade-offs and marginal rates of substitutions, such as willingness-to-pay (e.g., Reed et al., 2020) and willingness-to-sacrifice (e.g., Chorus et al., 2020) estimates, can be assessed. Lastly, the data collected using SP methods combine theory-driven hypotheses, high levels of experimental control and (statistical) efficiency to analyse trade-offs between multiple attributes. As argued by Gigerenzer (2010), moral dilemmas arise when different attributes are traded off one another, making moral decisions almost always multi-attribute. Thus, the SP methods are a promising data collection method for studying moral decision-making.

However, the conventional discrete choice approach and its models also have some weaknesses in studying moral decision-making. First, given that DCMs are structured by *a priori* assumptions, finding the optimal model specification is a rather time-consuming process. As an artefact of using suboptimal models, it could lead to erroneous and misleading model outcomes. Decision-makers can employ alternative decision rules, especially in moral decision-making (see Section 3.1). Therefore, several revisions are often required before the model is deemed fit-for-use, where its parameters are subject to sanity checks (e.g., signs and relative magnitudes). Second, the data collected using stated preference methods may contain unreliable reflections of moral decision-making. Given the hypothetical nature of the choice experiments, the choice tasks may not have enough consequentiality for decision-makers whose decisions do not reflect their preferences as they would in real-world decisions. Lastly, traditional DCMs solely rely on choice observations, for which challenges can occur in uncovering the full spectrum of moral decision-making. As discussed in Section 3.1, other psychological factors (e.g., moral convictions and motivations) also affect moral decision-making, which cannot be captured by choice observations alone.

3.3. Machine learning for discrete choice analysis

The remaining eighty-four articles (30%) of our review study used ML to model decision-making from a general perspective (Hillel et al., 2021; Van Cranenburgh et al., 2021; Wang et al., 2021a; Rodrigues et al., 2019; Aboutaleb et al., 2020a, 2020b; Ortelli et al., 2021). Most articles used types of ML models taken from the supervised learning paradigm (86%; e.g., Hensher and Ton, 2000; Wang et al., 2021a) to generate choice predictions, followed by unsupervised (2%; e.g., Sfeir et al., 2020) and reinforcement learning (1%; e.g., Adusumilli and Eckardt, 2019) paradigms. There were also nine articles (11%; e.g., Van Cranenburgh et al. (2021); Hillel et al. (2021)) that have not developed any ML models, as these are literature reviews or conceptual articles. The objectives of the articles ranged from comparing ML models against traditional DCMs on prediction performance and extracted behavioural insights (27%; e.g., Wang et al., 2021c; Brathwaite et al., 2017), strictly prediction performances (23%; e.g., Lee et al., 2018; Cantarella and de Luca, 2005), or extracted behavioural insights (1%; e.g., Alwosheel et al., 2019). Other articles (38%; e.g., Wong and Farooq, 2021; Sifringer et al., 2020) proposed methodological advancements to leverage ML for discrete choice analysis, while the remaining articles (11%; e.g., Athey, 2015; Athey and Imbens, 2019) were conceptual or conducted literature reviews. Given these objectives, it is not unexpected that most articles were methodological (70%; e.g., Lederrey et al., 2021; Ortelli et al., 2021; Berbeglia, 2018), while others were empirical (20%; e.g., Alwosheel et al., 2018; Barthélemy et al., 2018), conceptual (5%; e.g., Iskhakov et al., 2020), or literature reviews (5%; e.g., Hillel et al., 2021).

3.3.1. Review of the literature

The ML paradigm has recently gained the interest of the choice modelling community, showing that the usage of ML in the DCM paradigm is still in its infancy (Hillel et al., 2021; Van Cranenburgh et al., 2021). It seems to be a natural first step to compare ML and DCMs on predictive power, as one of the DCMs' objectives is to forecast choice behaviours. Indeed, most articles focused on comparing ML models against DCMs for generating choice predictions (Wang et al., 2021a; Wang et al., 2021b; Wang et al., 2020a; Wang et al., 2021c; Wang et al., 2020c; Wang et al., 2020c; Wong and Farooq, 2018, 2019, 2020, 2021; Wong et al., 2018; Lu et al., 2021b; Marques dos Santos et al., 2021; Kim and Kim, 2021; Zhu et al., 2020; Sifringer et al., 2020; Nam and Cho, 2020; Zhao et al., 2020; van Cranenburgh and Alwosheel, 2019; Zhang et al., 2020; Zhang and Xie, 2008; Ramsey and Bergtold, 2021; Alwosheel et al., 2021; Lhéritier et al., 2019; Lai et al., 2019; Lee et al., 2018; Wang and Ross, 2018; Cantarella and de Luca, 2005; Fish et al., 2004; Hruschka et al., 2002; Hensher and Ton, 2000; Subba Rao et al., 1998; Sun et al., 2018; Bentz and Merunka, 2000; Sfeir et al., 2020, 2021; Han et al., 2020; Lechner and Okasa, 2020; Barthélemy et al., 2018; Mottini and Acuna-Agost, 2017; Krueger et al., 2018; Brathwaite et al., 2017; Hagenauer and Helbich, 2017; Mohammadian and Miller, 2002; Yang and Klabjan, 2021; Zhang et al., 2017). These articles provide evidence that ML outperform DCMs in the goodness-of-fit; that is, prediction accuracies (Wang et al., 2021a; Wang et al., 2020c; Marques dos Santos et al., 2021) and obtains more accurate behavioural insights (Nam and Cho, 2020; Zhang et al., 2020; Ramsey and Bergtold, 2021; Lhéritier et al., 2019). Table 4 shows the types of ML methods used in the literature.

A variety of DCMs was used to compare against the ML models. One of the predominately used benchmark model types is the MNL model (Wang et al., 2021a; Wang et al., 2020a; Wang et al., 2020b; Wang et al., 2021c; Wong and Farooq, 2021; Lu et al., 2021b; Marques dos Santos et al., 2021; Zhu et al., 2020; Sifringer et al., 2020; Zhao et al., 2020; Zhang et al., 2020; Zhang and Xie, 2008; Alwosheel et al., 2021; Alwosheel et al., 2019; Lhéritier et al., 2019; Lai et al., 2019; Lee et al., 2018; Wang and Ross, 2018; Cantarella and de Luca, 2005; Fish et al., 2004; Hruschka et al., 2002; Subba Rao et al., 1998; Sun et al., 2018; Bentz and Merunka, 2000; Sfeir et al., 2020; Pereira, 2019; Barthélemy et al., 2018; Mottini and Acuna-Agost, 2017; Brathwaite et al., 2017; Hagenauer and Helbich, 2017), followed by MXL (Wang et al., 2021a, 2021b; Zhu et al., 2020; Zhao et al., 2020; Sfeir et al., 2020, 2021), LCL (Zhu et al., 2020; van Cranenburgh and Alwosheel, 2019; Lhéritier et al., 2019; Hruschka et al., 2002; Sfeir et al., 2020, 2021; Krueger et al., 2018), and nested logit (NL) models (Wang et al., 2021a; Wang et al., 2020c; Marques dos Santos et al., 2021; Zhu et al., 2018; Sifringer et al., 2020; Nam and Cho, 2020; Lai et al., 2019; Cantarella and de Luca, 2005; Hensher and Ton, 2000; Mohammadian and Miller, 2002). Some articles used more sophisticated DCMs, such as integrated choice and latent variable (ICLV) (Wong et al., 2018; Wong and Farooq, 2018) and dynamic models (Adusumilli and Eckardt, 2019). Most of the literature used the simplest class of DCMs (i.e., MNL) to show the potential of using ML models for generating choice predictions. Only recently have more sophisticated DCMs been used as a benchmark, which aims to validate the former and study how ML models perform compared to these DCMs based on capturing behavioural traits.

Table 4
(Un)supervised machine learning methods used in the literature.

Methods	N = 73[a]	%[b]	Reference(s)
Artificial Neural Networks	43	(74)	(Wang et al., 2021a; Wang et al., 2020a, 2020b, 2020c, 2021b, 2021c; Wong and Farooq, 2019, 2020, 2021; Marques dos Santos et al., 2021; Kim and Kim, 2021; Buijs et al., 2021; Sifringer et al., 2020; Nam and Cho, 2020; Zhao et al., 2020; van Cranenburgh and Kouwenhoven, 2021; van Cranenburgh, 2020; van Cranenburgh and Alwosheel, 2019; Zhang et al., 2020; Zhang and Xie, 2008; Ramsey and Bergtold, 2021; Alwosheel et al., 2018, 2019, 2021; Lai et al., 2019; Lee et al., 2018; Cantarella and de Luca, 2005; Fish et al., 2004; Kim and Kim, 2004; Vythoulkas and Koutsopoulos, 2003; Hruschka et al., 2002; Hensher and Ton, 2000; Subba Rao et al., 1998; Sun et al., 2018; Bentz and Merunka, 2000; Farrell et al., 2021; Han et al., 2020; Pereira, 2019; Barthélemy et al., 2018; Mottini and Acuna-Agost, 2017; Arkoudi et al., 2021; Hagenauer and Helbich, 2017; Mohammadian and Miller, 2002)
Decision Trees	15	(21)	(Wang et al., 2021a; Lu et al., 2021b; Marques dos Santos et al., 2021; Kim and Kim, 2021; Zhu et al., 2018; Zhao et al., 2020; Zhao et al., 2019; Lhéritier et al., 2019; Lai et al., 2019; Lee et al., 2019; Wang and Ross, 2018; Lechner and Okasa, 2020; Mottini and Acuna-Agost, 2017; Brathwaite et al., 2017; Hagenauer and Helbich, 2017)
Support Vector Machines	6	(8)	(Wang et al., 2021a; Zhao et al., 2020; Zhang and Xie, 2008; Lai et al., 2019; Sun et al., 2018; Hagenauer and Helbich, 2017)
Restricted Boltzmann Machines	4	(5)	(Wong and Farooq, 2018, 2019, 2020; Wong et al., 2018)
Naïve Bayes	3	(4)	(Wang et al., 2021a; Zhao et al., 2020; Hagenauer and Helbich, 2017)
K-Nearest Neighbours and K-Means Clustering	2	(3)	(Wang et al., 2021a; Buijs et al., 2021)

[a] Absolute number of articles.
[b] Relative number of articles (as % of 73 articles). Percentages do not add up to 100% because some articles used multiple methods.

ML models work comparatively well with large, unstructured, and high-dimensional datasets (and for some methods, it is even a requirement to have a large dataset) (Bishop, 2006). Therefore, it is not unexpected that most articles used RP data (Wong and Farooq, 2020; Wong and Farooq, 2019; Wong et al., 2018; Zhang and Xie, 2008; Cantarella and de Luca, 2005; Fish et al., 2004; Mohammadian and Miller, 2002). Some articles used SP (Wang et al., 2021c; Wong and Farooq, 2021; Weir and Sproul, 2019; Hensher and Ton, 2000; Han et al., 2020; Pereira, 2019) or combined SP and RP data (Wang et al., 2020c; Wong and Farooq, 2018; Sifringer et al., 2020; Bentz and Merunka, 2000; Sfeir et al., 2020). None of the articles was conducted in the health domain; instead, they were mostly applied to transport economics. Moreover, the sample sizes used ranged from 1015 to 1 million observations, compared to the sample sizes of the health-related DCM articles that ranged from 600 to 10,500 observations. See Appendix C for more detail on the sample sizes used per article.

While aggregated RP and SP datasets contain many choice observations (i.e., large dataset) and have a relatively high number of variables (i.e., high-dimensional), 'ordinary' RP and SP data are not unstructured. Some first steps have been taken to use unstructured data (i.e., text and image data), which are seldom analysed using DCMs as they are not naturally capable of handling such data types. Natural Language Processing (NLP) and Computer Vision (CV) models were used to analyse text and image data or address the interpretability issue of ML (Antonini et al., 2006; van Cranenburgh, 2020; Glerum et al., 2014). Van Cranenburgh (2020) proposed a method to incorporate visual stimuli in the discrete choice analysis by blending CV models into DCMs. For instance, visual stimuli affect decision-making when individuals book a tourist destination or hotel room online. Furthermore, Glerum et al. (2014) investigated the measurement of perceptions using adjectives freely reported by respondents in semi-open questions (i.e., text data).

Even though ML models can obtain higher predictive power and model fit than DCMs, model interpretability remains a challenge in the ML paradigm (Van Cranenburgh et al., 2021; Wang et al., 2021b; Aboutaleb et al., 2021). The literature shows two directions addressing this issue: i) integration and ii) complementation. The former direction developed hybrid models that incorporated an ML component into DCMs with imposed functional forms and used interpretability techniques to extract behavioural insights from the ML models (Wang et al., 2020a, 2020b, 2021c; Sifringer et al., 2020; Zhao et al., 2019; Alwosheel et al., 2019, 2021; Han et al., 2020; Pereira, 2019; Arkoudi et al., 2021). The latter stream examined whether ML methods can complement DCMs in the model-building procedure (Rodrigues et al., 2019; Aboutaleb et al., 2020a, 2020b; Ortelli et al., 2021). For instance, Aboutaleb et al. (2020a) proposed a nested logit structure discovery method using a data-driven approach instead of relying on *a priori* assumptions. Other studies have made similar attempts by proposing optimisation approaches to assist in specifying and estimating DCMs (Lederrey et al., 2021; Weir and Sproul, 2019; Chiong and Shum, 2019; Tan, 2017; Xie et al., 2021; Yang et al., 2017; Braun and McAuliffe, 2010; Hancock and Hess, 2021; Hancock et al., 2020b).

The literature rarely explores models and techniques from the unsupervised and reinforcement learning paradigms. Some articles used semi-supervised ML, combining supervised and unsupervised learning methods, to account for preference heterogeneity in the data (Sfeir et al., 2020, 2021; Krueger et al., 2018). For instance, Sfeir et al. (2021) used a semi-nonparametric LCL model based on a Gaussian process to improve representations of unobserved heterogeneity. Also, some first steps have been taken to use reinforcement learning for dynamic discrete choice modelling to learn and explain decision-making processes (Adusumilli and Eckardt, 2019).

3.3.2. *Strengths and weaknesses of machine learning*

Even though the current body of ML-related literature has yet to acknowledge and explore the moral dimensions of decision-making, the ML paradigm has clear potential for studying decision-making. First, the ML models often obtain higher prediction accuracies and goodness-of-fit than conventional DCMs. This result indicates that ML models are comparatively better at capturing the underlying decision process (i.e., data generating process). For instance, Wang et al. (2021a) found that DCMs achieve lower prediction accuracies and have much longer computational time when sample sizes increase than ML models.

Second, ML models can overcome the problems of DCMs in the search for the optimal model specification. DCMs contain functional forms and variable selection imposed by *a priori* assumptions, where model misspecifications can lead to erroneous model outcomes. In contrast, ML models learn patterns from the data more flexibly and accurately without any prior assumptions, making them more efficient, less cumbersome, and time-consuming to find the optimal model specification (e.g., Sifringer et al., 2020).

Third, ML models work well and more efficiently with large datasets, which is of utmost importance as datasets are becoming larger and more complex (e.g., using RP data) (Wang et al., 2021a; Lederrey et al., 2021). Finally, ML models can work with unstructured data, which are currently outside the realm of DCMs. Using data sources like text and images opens the opportunity to obtain more insights into decision-making (van Cranenburgh, 2020; Glerum et al., 2014).

However, ML models also have a weakness in studying decision-making. The previous subsection has shown that model interpretability remains challenging; most ML models are 'black-box' models (Van Cranenburgh et al., 2021; Wang et al., 2021b; Aboutaleb et al., 2021). Even though first attempts have been made to use interpretability techniques to extract behavioural insights from the ML models (Wang et al., 2020a, 2020b, 2021c; Sifringer et al., 2020; Zhao et al., 2019; Alwosheel et al., 2019, 2021; Han et al., 2020; Pereira, 2019; Arkoudi et al., 2021), much has still to be explored. Especially for health economics, as none of the ML-related articles was applied to healthcare decisions.

3.4. *Research agenda for choice modellers*

The previous subsections' literature review, where the synthesized results are validated by the included articles obtained in the scoping searches, provides several research directions to bridge the gap between DCMs and ML for studying moral decision-making. We will address the directions found based on the strengths and weaknesses of both modelling paradigms.

One direction for future research is to find and deepen the utility function by combining DCMs and ML. As discussed in Section 3.2.2, the discrete choice approach has some strengths and weaknesses in studying moral decision-making. The specifications of DCMs are driven by *a priori* assumptions to ensure that the models hold behaviourally sound information. However, finding the optimal model specification is a rather time-consuming process, where suboptimal models can lead to erroneous and misleading outcomes. Although the choice modelling community has put much effort into inferring various rational and boundedly rational model specifications, DCMs are still limited to one predefined utility function (Abou-Zeid and Ben-Akiva, 2011; Cameron and DeShazo, 2010; Cantillo, 2005; Chorus and van Cranenburgh, 2014; Chorus, 2010; Fishburn, 1975; Fishburn, 1971; Gigerenzer and Selten, 2001; Gilbride and Allenby, 2004; Hensher et al., 2010; Hensher and Rose, 2012; Hess et al., 2013; Hess et al., 2012; Hole, 2011; Huber et al., 1982; Kivetz et al., 2004; Leong and Hensher, 2012; Louviere et al., 2008; Rooderkerk et al., 2011; Russo and Dosher, 1983; Scarpa et al., 2009; Simon, 1955; Simonson and Tversky, 1992; Swait and Marley, 2013; Swait, 2009; Swait and Adamowicz, 2001; Swait, 2001; Swait and Ben-Akiva, 1987; Tversky and Simonson, 1993; Tversky and Kahneman, 1991; Tversky, 1972; Tversky, 1969; Manski, 1977). It is expected, however, that the utility function describing moral decision-making differs across decision-makers and decision situations. As argued by Schwartz (1968) and Gigerenzer (2010), the framing of decisions determines if and which moral rule is employed in the decision-making. Future research should thus aim to infer which moral decision rule applies when and for whom. ML could be considered a promising way forward by integrating unsupervised learning methods into DCMs to discover latent choice patterns more flexibly and without making prior.

ML models can also be used to consider the 'moral' cost and benefit in the utility function by capturing systematic moral heterogeneity. DCMs capture systematic heterogeneity by specifying interactions between different pairs of variables. For instance, an interaction between cost and the level of altruism (Philippe Rushton et al., 1981) or scores on moral foundations (Graham et al., 2013) to account for one's moral attitude. However, the model-building process quickly becomes infeasible as the number of testable higher-order interactions grows exponentially with the number of explanatory variables. ML models can be used to overcome this challenge, as they can discover complex higher-order interactions from the data as part of the training process. Some scholars have made the first attempts by using artificial neural networks (Wang et al., 2020a; Sifringer et al., 2020; Han et al., 2020).

Before pursuing these research directions, the first question that must be answered is whether we can extract behavioural valuations from ML models. Especially considering that model interpretability remains challenging in ML. In contrast, DCMs carry clear subject-matter interpretations from which 'direct' valuations can be extracted, such as behavioural interpretations of the estimated utility weights. The 'indirect' valuations can also derive marginal rates of substitutions (e.g., willingness-to-pay and willingness-to-sacrifice). Although earlier research efforts focused on extracting behavioural and economic insights from ML models, whether the models can extract health economic information, such as QALY measures and other values of health outcomes, remains unexplored. One potential direction relates to the developments of explainable artificial intelligence (XAI) or the so-called model-agnostic methods, making, e.g., SHAP values (Lundberg and Lee, 2017), variable importance scores (Wei et al., 2015), and local surrogate models (Ribeiro et al., 2016), a particularly fruitful way forward.

Another research direction is enriching the insights from DCMs by using ML and considering intrapersonal factors. As discussed in Section 3.2, DCMs solely rely on choice observations, for which these models cannot uncover the full spectrum of moral decision-making. We found that other psychological factors, such as moral convictions and values, can affect one's decision-making when facing moral decisions (Conway et al., 2018; Faust and Menzel, 2011; Rogerson et al., 2011; Musschenga, 2005; Papaoikonomou et al., 2011; Cosentino et al., 2020; Roets and Bostyn, 2020; Bostyn and Roets, 2017; Crockett, 2016; Bénabou and Tirole, 2011; Tinghög et al., 2016; Schwartz, 2016). ML models can be utilised to obtain insights into these psychological factors, as they can handle unstructured and high-dimensional data sources (Bishop, 2006). For instance, ML can enrich the insights from DCMs by including written expressions obtained from (semi-)open questions, where one can elaborate on their decision, using Natural Language Processing (NLP) models. In many choice situations, visual information can affect moral decision-making. The Computer Vision (CV) models are attractive in these cases, as sight perceptions can be extracted from image and video data. Thus, using model types from NLP and CV, psychological constructs such as moral convictions and values can improve the behavioural realism of DCMs.

Aggregating SP and RP data is another fruitful direction to explore for studying moral decision-making. SP methods, like discrete choice experiments, have ups and downsides (see Section 3.2 for the discussion). The downside of using SP methods is that the data collected may lack external validity, given the hypothetical nature of the experiments. Aggregating SP and RP data may improve the external validity of the results. While DCMs lack the efficiency to work well with large datasets, ML models can be used and address the issues raised about whether experimental data yield externally valid results (Bauman et al., 2014; Huebner et al., 2009; Kahane and Shackel, 2010).

So far, we have only considered DCMs and ML models in static choice scenarios. However, moral decisions are likely to be consequential (Capraro and Perc, 2021). Modelling moral decision-making in a dynamic choice context, where a decision-maker must make sequential choices in changing scenarios with (future) consequences that may or may not affect himself, captures the evolution of decision-making over time. In the paradigm of DCMs, dynamic choice models are used to obtain insights into the effects of changing external factors (e.g., social influences), learning, and forward-looking behaviour (Ben-Akiva et al., 2002). As these traditional models are constrained by their assumptions and estimation complexity, combining the models with practices from ML seems to be a very promising research endeavour. Mainly, reinforcement learning methods, which are about learning the 'optimal' behaviour in an environment to obtain the maximum reward, are a worthwhile research direction to understand and explain moral decision-making processes.

4. Discussion

In this review study, containing 277 articles, we pinpointed the strengths and weaknesses of DCMs and ML for moral choice analyses based on the identified characteristics of moral decision-making. This resulted in a research agenda that lays out the directions for future research to bridge the gap between the DCM and ML paradigm.

Based on our findings, we argue that moral decision-making is more complex than 'regular' decision-making. We found that moral preferences follow (social) norms about what one thinks to be the right thing to do. In contrast, from the perspective of the RUT underlying the traditional DCMs, personal preferences are based on strict self-interest and the interest of close one (Harsanyi, 1976; Capraro and Perc, 2021). The moral dimension of decisions determines if and which moral rules are employed in decision-making. Decision-makers can use alternative decision strategies (e.g., Gigerenzer, 2010). Insights from psychology showed that moral decision-making could either follow controlled (deliberative) or automatic (emotional and intuitive) processes, where deliberative reasoning can occur ex-post facto (Haidt, 2001; Greene et al., 2001, 2004). Other psychological factors (e.g., moral convictions and values) also affect moral decision-making.

Combining DCMs and ML has the potential to study moral decision-making more accurately and better inform health policy decisions. We found that finding the DCMs' optimal model specification – guided by prior beliefs and theories to ensure behavioural soundness in the models - is a rather time-consuming process. Although the RUT underlying the discrete choice approach can be related to utilitarianism, where both prescribe actions to maximise some outcome, the paradigms differ in their semantics. RUT considers that personal preferences are maximised, while utilitarianism follows moral preferences where outcomes are maximised for all affected decision-makers (McFadden, 1974, 1981; Conway and Gawronski, 2013; Marseille and Kahn, 2019; Harsanyi, 1975). Specifically, moral decision-making involves what one believes to be the right thing to do. Different alternative decision rules can be employed in the decision-making, making the model specification process cumbersome. Whilst DCMs hold clear behavioural interpretations and many alternative decision rules exist for specifying the models (e.g., the taboo trade-off aversion (Chorus et al., 2018; Chorus et al., 2020) and random regret minimisation (Chorus, 2010)), they are prone to provide erroneous model outcomes caused by model misspecifications.

In contrast, we found that ML models obtain comparatively higher prediction accuracies and have more model flexibility (e.g., Wang et al., 2021a). ML models learn patterns from the data more flexibly and accurately without prior assumptions. As argued by Aboutaleb et al. (2021) and shown by, for example, Sifringer et al. (2020), ML can be leveraged in specifying and systematically selecting the optimal model specification more efficiently. One weakness of ML is that most models are 'black boxes'; they lack model interpretability and explainability. We found that the first attempts have been made to extract behavioural insights from ML models (e.g., Alwosheel et al., 2021, 2019), but much has still to be explored. Especially in healthcare, where the impacts of decisions are critical, model interpretability is required.

We also found that all empirical health-related DCM articles collected data using SP methods like discrete choice experiments and profile case best-worst scaling. Although the experimental control is helpful, the data may be prone to hypothetical bias. The decisions may not reflect the moral preferences one would have in real-world decisions (Haghani and Sarvi, 2019). Moreover, relying solely on choice observations causes DCMs not fully unravel moral decision-making, knowing that other psychological factors (e.g., moral convictions and values) affect moral decision-making. In contrast, ML models work well with large datasets, making them potentially useful when aggregating RP and SP data. Also, ML models can handle alternative data sources like text and image data, which are currently outside the realm of DCMs. Some first attempts have been made to combine DCMs and ML models for leveraging text and image data (van Cranenburgh, 2020; Glerum et al., 2014). Especially the latter seems promising for obtaining more profound insights into moral decision-making, as visual stimuli and psychological constructs such as moral convictions and perceptions affect moral decision-making processes. Hence, the strengths of ML are necessary for the discrete choice approach to obtain more accurate insights into moral decision-making.

Based on this review, a research agenda for choice modellers in health economics (and beyond) can be summarised as follows: first, choice modellers should explore whether health economic information, such as QALY measures and other values of health outcomes, can be extracted from ML models using explainable AI methods. As discussed, model interpretability is crucial for (public) healthcare decisions. Second, choice modellers could explore if and which moral decision rules are employed in the given decision environment, using the flexibility of ML and without making prior assumptions. Third, choice modellers could explore whether ML models can be used to capture systematic moral heterogeneity. For instance, moral attitudes can be incorporated by specifying interactions between the level of altruism (Philippe Rushton et al., 1981) and other attributes. Fourth, choice modellers could explore alternative data sources like text and image data by combining ML models and DCMs, considering that other psychological constructs (e.g., moral convictions and values) affect moral decision-making. Fifth, choice modellers could use ML models to aggregate SP and RP data and improve the external validity of the analysis on moral decision-making. Lastly, choice modellers could move beyond static choice scenarios and explore the use of ML models (especially reinforcement learning methods) in dynamic, sequential choice scenarios, capturing the evolution of moral decision-making (and preferences) over time.

Some limitations of this review require discussion. The first limitation is that relevant articles may have been overlooked for various reasons. We found that none of the ML-related literature was applied to (public) healthcare decisions. Compared to the field of health economics, the number of ML-related publications has exponentially increased over the years in transport economics (Hillel et al., 2021; Van Cranenburgh et al., 2021). The research endeavours on the intersection of DCMs and ML are emerging quickly. Therefore, articles concerning our review study may have been published after we finalised the searches in April 2021. Another reason is related to the search queries used in our study, as they may be subject to selection bias. We defined the search queries on whether the searches found preselected key articles, where the key articles were determined based on the expertise of each author and an independent external researcher.

The second limitation is that the data extraction and interpretation of the results should be carefully interpreted. For pragmatic reasons, the first author extracted the data, followed by crosschecking and confirmation of the other authors. Whilst data extraction was designed to be as objective as possible, we analysed the main conclusions of the included articles to obtain more in-depth insights. There could be discrepancies between what the authors of the articles meant, how we interpreted their conclusions, and how other researchers would interpret them.

Finally, the third limitation is that the supplementary dataset may have introduced some bias in the results of our review. We followed a robust and structured search methodology to prevent the results from any type of bias. We believe that gathering as many data points as possible can validate the findings from the systematic search strategy.

5. Conclusion

In conclusion, this paper highlights that combining DCMs and ML has clear potential to obtain richer insights into moral decision-making and better inform health policy decisions when moral dilemmas occur. By providing a research agenda, we have argued that ML can be used to i) find and deepen the utility specification of DCMs, and ii) enrich the insights extracted from DCMs by considering other psychological factors of moral decision-making. The next steps are to bridge the gap between DCMs and ML, and increase their appeal and applicability in health economics, where humans and machines meet each other.

Author contributions

Nicholas V.R. Smeele: Conceptualization, Investigation, Writing – original draft. Caspar G. Chorus: Conceptualization, Investigation, Writing – review & editing, Funding acquisition, Supervision. Maartje H. N. Schermer: Conceptualization, Writing – review & editing, Funding acquisition, Supervision. Esther W. de Bekker-Grob: Conceptualization, Investigation, Writing – review & editing, Funding acquisition, Supervision.

Data availability

The extracted data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2023.115910.

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