

## Special Interest Project – Research Article

Lending (and consequently, debt) in Australia is a part of everyday life. It is most people's dream to be able to take out a mortgage and purchase a home. As a result of this, in March 2022 alone, there was \$33.28B of new borrower-accepted loan commitments for residential housing (seasonally adjusted), of which \$21.57B was by owner occupiers, and \$11.71B was investors. There was \$2.29B of personal fixed term loans, whilst there was \$9.13B of business loans (construction and property purchase).<sup>1</sup> Australia's household debt-to-income ratio is currently in the top quartile of the world.<sup>2</sup>

No matter how a decision is made regarding the credit to extend to an applicant (i.e. whether to give credit, and if so, the terms on which it is provided) (the **lending decision**), a voluminous amount of data and information is used by the potential lender.

In terms of the information that is used, the credit score of an applicant has been the dominant piece of information used when assessing the “five C's” that the lender will consider. However, the Office of the Comptroller of the Currency (**OCC**), part of the US Department of Treasury, has questioned the traditional dominance of the credit score. The OCC has noted that people who lack a credit score struggle to obtain credit, but that they are paying rent, utilities and financial obligation on time. These on-time payments could be used as an alternative to the traditional credit score. The OCC noted that there are 45-65 million people in the US with “either no credit file or a very thin credit file”, most of which are minorities. Therefore, this is a point worth considering, especially when considering the impact of AI in the lending decision.<sup>3</sup>

Using the credit score, and potentially (moving forward) other types of information such as on-time bill payments, lenders engage in a due diligence process as part of the lending decision. The veracity of the due diligence will depend on the size and potential risk of the particular loan, however, potential lenders tend to consider the “five C's”: character, capacity, capital, condition, and collateral. The first three are part of the quantitative financial analysis, whilst the other two involve a qualitative analysis.<sup>4</sup> Further information on each of these factors is contained in the attached research brief.

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<sup>1</sup> Australian Bureau of Statistics, *Lending Indicators, March 2020* (Catalogue No 5601.0, 4 May 2022).

<sup>2</sup> Jonathan Kearns, Mike Major and David Norman, 'How Risky is Australian Household Debt?' (Research Discussion Paper 2020-05, Reserve Bank of Australia, August 2020) 4.

<sup>3</sup> 'OCC Working With Tech Firms on Credit Score Alternatives', *American Bankers Association* (Web Page, 25 June 2021) <<https://bankingjournal.aba.com/2021/06/occ-working-with-tech-firms-on-credit-score-alternatives/>>.

<sup>4</sup> John E. Baiden, 'The 5 C's of Credit in the Lending Industry' (Research Report, 26 June 2011) 10 <[https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1872804](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1872804)>.

Discriminatory practices and results have occurred in lending decisions for a very long time. There have been many barriers inhibiting those with a protected characteristic from obtaining credit, or obtaining credit on equally favourable terms. Such examples include those of a minority race (with race being a protected characteristic) or being a woman (with sex and gender also being a protected characteristic). For example, a 1990 study conducted in the United States confirmed that black and Hispanic applicants did not enjoy the same general presumption of creditworthiness, and that lenders were more willing to overlook flaws for white applicants than for minority applicants. It also confirmed that even after controlling for financial, employment, and neighbourhood characteristics, black and Hispanic mortgage applicants in the Boston metropolitan area were roughly 60 percent more likely to be turned down than whites.<sup>5</sup>

Entities who use AI which discriminates against protected characteristics are putting themselves at risk of various legal, financial, and reputational risks.<sup>6</sup> Contrarily, it has been noted that reducing bias in the use of AI is socially and fiscally responsible, as “early movers in reducing bias through AI will have a real competitive advantage on top of doing their moral duty”.<sup>7</sup>

As noted above, a lot of information and data is provided by an applicant which is then “crunched” to assist a lender make its lending decision. Financial institutions are now using artificial intelligence and machine learning (collectively, **AI**) to assist with the lending decision, by improving the veracity and efficiency and decision making.

On the most basic level, AI is “the study of agents that receive percepts from the environment and perform actions.”<sup>8</sup> Specifically in the context of AI in the lending decision, lenders are increasingly using algorithms, which means “a process of procedures that extracts patterns from data”. These algorithms are supervised machine learning models which use past examples to predict an outcome.<sup>9</sup> In lending, this outcome most likely refers to whether a potential loan would be profitable for a lender, or if it would be too risky.

Therefore, lenders are using these algorithms to assist in making the lending decision and in assessing the Five C’s. The below quote from the Australian Human Rights Commission

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<sup>5</sup> David K Horne, ‘Evaluating the Role of Race in Mortgage Lending’ (1994) 4 *FDIC Banking Review* 1. See also Alicia H Munnell et al, ‘Mortgage Lending in Boston: Interpreting HMDA Data’ (1992) 92(7) *Federal Reserve Bank of Boston* 25.

<sup>6</sup> Australian Human Rights Commission, ‘Using artificial intelligence to make decisions: Addressing the problem of algorithmic bias’ (Technical Paper, November 2020) 16 (‘AHRC’).

<sup>7</sup> Sian Townson, ‘AI Can Make Bank Loans More Fair’ *Harvard Business Review* (Web Page, 6 November 2020) <<https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair>>.

<sup>8</sup> Stuart Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach* (Pearson, 3<sup>rd</sup> ed, 2010), viii.

<sup>9</sup> Michelle Seng Ah Lee and Luciano Floridi, ‘Algorithmic Fairness in Mortgage Lending: from Absolute Conditions to Relational Trade-offs’ (2021) 31 *Minds and Machines* 165, 170.

accurately captures part of the mechanics of how AI is used by institutions during the lending decision:

*“For example, an AI system that assists a bank in deciding whether to grant people home loans typically is trained on the bank’s previous loan decisions, as well as any other data that the bank has access to. This can help the bank determine risk of default, by reference to an applicant’s financial and employment history, and demographic information. In this way, the AI system can identify feature values or indicia associated with decisions to offer loans to people who turn out to be profitable (or unprofitable) for the bank. When the bank considers a new applicant for a bank loan (sometimes referred to as ‘query data’), the AI system can be used to consider those feature values or indicia as they apply to the applicant, with a view to predicting whether the new applicant would be likely to pay back their loan reliably”.*<sup>10</sup>

Each of the big four banks have made comments in the media regarding their use of AI in lending decisions, for example:

- Commonwealth Bank of Australia (**CBA**) – CBA has an exclusive partnership with H2O.ai, a global leader in AI,<sup>11</sup> and CBA’s lending decisions “are now automated for approximately 65 per cent of home loans coming through the proprietary channel”<sup>12</sup>;
- The Australia and New Zealand Banking Group (**ANZ**) – ANZ uses a machine learning process in its lending decision procedure, and believes that once the technology completes the procedure, it can make a decision in four seconds.<sup>13</sup> Its New Zealand arm is working with Bud to streamline its lending process. The Bud system will upload borrowers’ statements, and its intelligence tool will enrich the statement data, identify and categorise income and expenses, and provide a summary to ANZ;<sup>14</sup>

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<sup>10</sup> AHRC (n 6) 10.

<sup>11</sup> ‘CBA partners with global AI leader H2O.ai’, *Commbank* (Web Page, 8 November 2021) <<https://www.commbank.com.au/articles/newsroom/2021/11/CBA-partners-AI-leader.html#:~:text=We%20will%20be%20using%20our,as%20Amber%20Energy%20and%20CoGo.%E2%80%9D>>.

<sup>12</sup> Annie Kane, ‘ANZ looks to AI to automate home loan process’ *The Adviser* (Online, 13 April 2021) <<https://www.theadviser.com.au/lender/41462-anz-looking-at-ai-to-automate-home-loan-process>>.

<sup>13</sup> *Ibid.*

<sup>14</sup> Polly Jean Harrison, ‘Bud and ANZ NZ Sign Strategic AI Deal to Streamline Lending Process’ *The Fintech Times* (online, 18 February 2021) <<https://thefintechtimes.com/bud-and-anz-nz-sign-strategic-ai-deal-to-streamline-lending-process/>>.

- Westpac – Westpac uses AI “to make smarter decisions by accurately assessing several data points at lightning speed, whilst reducing human error”;<sup>15</sup> and
- National Australia Bank (NAB) – NAB will use a system created by Rich Data (a Sydney-based AI company) to assist with real-time loan assessment, taking data from “cloud accounting platforms, transaction systems and other macroeconomic sources to profile small to medium enterprises and predict their likelihood of repayment.”<sup>16</sup>

It is therefore clear that each of the big four banks (and most likely smaller banks and fintechs) are using AI in their lending decision, primarily for the sake of efficiencies and accuracy.

As noted above, discrimination has historically occurred in the practice of lending, both in terms of the decision whether to provide credit, and the terms on which any credit is offered. The problem with using AI in lending is that AI systems often experience the same historical biases that have been historically present in lending. This is because the data populated into AI systems is the same data which reflects the biases of the historical lending framework. The focus should therefore be on “less historic accuracy but greater equity” when providing loans.<sup>17</sup> Similarly, Dr Catriona Wallace (founder of Flamingo AI, an AI business partner of Westpac) stated that a key challenge around machine learning is that “it’s built through supervised training, or data fed by a human that effectively acts as a teacher, raising the issue of conscious or unconscious bias being passed on”. Dr Wallace goes on to say that AI Flamingo and Westpac seek to challenge this through ensuring the data being used to code the machine is free from bias, and having a diverse range of people represent the teams responsible for AI development.<sup>18</sup>

The culmination of the above is that historical biases have been “baked” into the data set from which AI systems make their decision, which is purportedly free of bias or discrimination. How this occurs is best elicited by summarising a proposed solution proffered by Sian Townson at the Harvard Business Review, which is as follows:<sup>19</sup>

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<sup>15</sup> 'Data and AI: The next revolution', *Westpac IQ* (Web Page, 26 July 2021) <<https://westpaciq.westpac.com.au/Article/48825#:~:text=Launched%20in%20late%202019%2C%20the,any%20harm%20caused%20by%20AI>>.

<sup>16</sup> James Evers, 'NAB turns to AI to decide on small business loans', *Australian Financial Review* (online, 8 December 2020) <<https://www.afr.com/companies/financial-services/nab-turns-to-artificial-intelligence-to-assess-small-business-loans-20201204-p56kkm>>.

<sup>17</sup> Townson (n 7).

<sup>18</sup> Emma Ringland, 'Ethics, diversity key as AI takes hold', *Westpac* (Web Page, 3 July 2019) <<https://www.westpac.com.au/news/making-news/2019/07/ethics-diversity-key-as-ai-takes-hold/>>.

<sup>19</sup> Townson (n 7).

### **Step One - remove bias from the data before the model is built:**

Creators and users of AI systems need to do more than remove data variables which clearly indicate a protected characteristic (such as gender or ethnicity) because previous biases ripple through that data. For example, women usually have lower sample loan data because institutions have historically approved fewer and smaller loans for females than men with equivalent applications. This can lead to false (negative) inferences being drawn by the AI system against that particular applicant. AI can be used to spot and correct patterns of historical discrimination in the raw data, thereby balancing the data to create the more equitable credit position that the particular lender (hopefully) desires.

### **Step Two – pick better goals for models that discriminate:**

This step explains how even when the data has been adjusted in line with the above, remaining biases can still creep in. In order to prevent this, banks can create an algorithm which aims to fit historical data and score well on a measure of “fairness”. This step would include a parameter which penalises the model if it treats protected classes (those with a protected characteristic) differently. However, a potential limitation of this step (as identified by Townson) is that algorithms may not be able to identify which definitions of fairness to use, or which groups it should protect. In this scenario, the AI system may actually cement the biases it intends to eliminate.

### **Step Three – introduce an AI-driven adversary**

Here, an AI-driven adversarial model is created to predict protected class bias in the primary model. If this adversary can detect a protected characteristic from how the first credit model treats an applicant, the original model is corrected. For example, adversaries can often detect ethnic minority ZIP codes in the United States from the outputs of the original model. The idea is that this step can help re-tune the model to increase the influence of variables which contribute to equity and reduce those that contribute to bias.

Now that we understand how discrimination can occur through the use of AI, we should consider whether the use of AI has actually affected the prevalence of discrimination in lending. One study from the University of Berkeley found that algorithms used by fintech lenders (who are more likely to rigorously utilise AI) discriminate 40% less than face-to-face lenders, partly due to the removal of face-to-face interactions. However, the study also found that Latinx and African-Americans pay 5.3 and 2.0 basis points higher for mortgage and refinance mortgages, respectively, originating on Fintech platforms.<sup>20</sup>

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<sup>20</sup> Robert Bartlett et al, ‘Consumer-lending discrimination in the FinTech Era’ (Working Paper, November 2019) 29.

It is now important to consider the legal basis on which “discrimination” as a concept is protected in Australia. At common law, “the essence of the legal notion of discrimination lies in the unequal treatment of equals, and, conversely in the equal treatment of unequals”.<sup>21</sup> The essence of Australia’s statutory anti-discrimination scheme is the prohibition on discrimination through some associated conduct, and the remedies are primarily established as civil wrongs rather than criminal acts.<sup>22</sup>

There are several pieces of Commonwealth legislation which each deal with a specific area of discrimination (e.g. race or sex), whilst each state and territory has a piece of legislation which deals with various aspects and types of discrimination (e.g. the *Anti-Discrimination Act 1977* (NSW)). For there to be discrimination under the respective Commonwealth or state legislative schemes, there must be two things. Firstly, there must be a valid attribute of the complainant which is “protected” as a matter of law, for example race or age. Then, discrimination (which can take many forms, such as direct or indirect) must occur in a covered area – i.e. a specific situation in which discrimination against the aforementioned characteristic is protected.

Relevant to lending, it is unlawful to discriminate (whether in refusing to provide goods or services absolutely or the terms on which such goods or services are offered) on the following bases when providing **goods or services** to a person:

- Race, colour ethnic origin or that person or their relatives or associates;<sup>23</sup>
- Sex, sexual orientation, gender identity, intersex status, marital or relationship status, pregnancy or potential pregnancy, or breastfeeding;<sup>24</sup>
- Disability;<sup>25</sup>
- Age;<sup>26</sup> and
- In the *Anti-Discrimination Act 1977* (NSW) – all protected attributes in that Act, other than carer responsibility. Note – there is equivalent legislation for other states and territories not considered in this research.

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<sup>21</sup> *Castlemaine Tooheys Ltd v South Australia* (1990) 169 CLR 436, 480 (Gaudron and McHugh JJ).

<sup>22</sup> Beth Gaze and Belinda Smith, *Equality and Discrimination Law in Australia: An Introduction* (Cambridge University Press, 1<sup>st</sup> ed, 2017) 51.

<sup>23</sup> *Racial Discrimination Act 1975* (Cth) s 13.

<sup>24</sup> *Sex Discrimination Act 1984* (Cth) s 22.

<sup>25</sup> *Disability Discrimination Act 1992* (Cth) s 24.

<sup>26</sup> *Age Discrimination Act 2004* (Cth) s 28.

Notwithstanding this, there are several exceptions in relation to credit applications on the basis of **age** where the decision is based on actuarial or statistical data:

- *Age Discrimination Act 2004* (Cth) – s37(4)-(5);
- *Anti-Discrimination Act 1977* (NSW) – s49ZYU; and
- *Equal Opportunity Act 2010* (Vic) – s48.

The culmination of the above provisions is that it will not be unlawful to discriminate on the basis of age in respect of the lending decision if that discrimination is based on actuarial or statistical data. However, there is no exception in relation to credit application for all other protected attributes listed above. This means that it will be unlawful for a credit provider to discriminate against any of those categories (other than age) when considering whether to provide credit. This is important in the historical background where a lot of people have been subject to unfair discrimination in the lending market, particularly on the basis of sex/gender and race (both of which are protected attributes).

Due to the “soft-law” approach to AI which Australia has followed to date, the Department of Industry, Science, Energy and Resources has developed “Australia’s Artificial Intelligence Ethics Framework” (“**the Framework**”)<sup>27</sup>, a voluntary set of principles which organisations can sign up to. The Framework is intended to be aspirational, and its principles are designed to ensure AI is safe, secure and reliable. Table 4C in the attached research brief provides a summary of each of the 8 AI Ethics Principles and a note on how each relates to the use of AI in lending. Signatories to the Framework who provide (or are adjacent to the provision of) credit include NAB, the Commonwealth Bank of Australia (**CBA**), and Flamingo AI. However, I have found nothing stating that ANZ or Westpac are signatories to the Framework.

It is encouraging that both Westpac and NAB have made comments in the media as to the ethics of using AI in lending and things they consider when using AI. However, it is disappointing that CBA and ANZ’s public comments pertain only to the increased efficiencies which arise from using AI, rather than the ethical considerations. Lastly, it is also disappointing that none of the big four banks have an official policy on their AI systems used in lending, or how they intend to ensure their systems do not discriminate. Such accountability and transparency would be broadly consistent with the Framework, specifically principles 6 and 8.

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<sup>27</sup> 'Australia’s Artificial Intelligence Ethics Framework', *Department of Industry, Science, Energy and Resources* (Web Page) < <https://www.industry.gov.au/data-and-publications/australias-artificial-intelligence-ethics-framework/australias-ai-ethics-principles>>.

## BIBLIOGRAPHY

### A *Articles/Books/Reports*

Australian Human Rights Commission, 'Using artificial intelligence to make decisions: Addressing the problem of algorithmic bias' (Technical Paper, November 2020)

Baiden, John E., 'The 5 C's of Credit in the Lending Industry' (Research Report, 26 June 2011) 10 <[https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1872804](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1872804)>

Bartlett, Robert, et al, 'Consumer-lending discrimination in the FinTech Era' (Working Paper, November 2019)

Eyers, James, 'NAB turns to AI to decide on small business loans', *Australian Financial Review* (online, 8 December 2020) <<https://www.afr.com/companies/financial-services/nab-turns-to-artificial-intelligence-to-assess-small-business-loans-20201204-p56kmk>>

Gaze, Beth and Belinda Smith, *Equality and Discrimination Law in Australia: An Introduction* (Cambridge University Press, 1<sup>st</sup> ed, 2017)

Harrison, Polly Jean, 'Bud and ANZ NZ Sign Strategic AI Deal to Streamline Lending Process' *The Fintech Times* (online, 18 February 2021) <<https://thefintechtimes.com/bud-and-anz-nz-sign-strategic-ai-deal-to-streamline-lending-process/>>

Horne, David K, 'Evaluating the Role of Race in Mortgage Lending' (1994) 4 *FDIC Banking Review* 1

Kane, Annie, 'ANZ looks to AI to automate home loan process' *The Adviser* (Online, 13 April 2021) <<https://www.theadviser.com.au/lender/41462-anz-looking-at-ai-to-automate-home-loan-process>>

Kearns, Jonathan, Mike Major and David Norman, 'How Risky is Australian Household Debt?' (Research Discussion Paper 2020-05, Reserve Bank of Australia, August 2020)

Munnell, Alicia H, et al, 'Mortgage Lending in Boston: Interpreting HMDA Data' (1992) 92(7) *Federal Reserve Bank of Boston* 25

Russell, Stuart, and Peter Norvig, *Artificial Intelligence: A Modern Approach* (Pearson, 3<sup>rd</sup> ed, 2010)

### B *Cases*

*Castlemaine Tooheys Ltd v South Australia* (1990) 169 CLR 436



## **C Legislation**

*Age Discrimination Act 2004* (Cth)

*Anti-Discrimination Act 1977* (NSW)

*Disability Discrimination Act 1992* (Cth)

*Equal Opportunity Act 2010* (Vic)

*Racial Discrimination Act 1975* (Cth)

*Sex Discrimination Act 1984* (Cth)

## **D Other**

Australian Bureau of Statistics, *Lending Indicators, March 2020* (Catalogue No 5601.0, 4 May 2022)

'Australia's Artificial Intelligence Ethics Framework', *Department of Industry, Science, Energy and Resources* (Web Page) <<https://www.industry.gov.au/data-and-publications/australias-artificial-intelligence-ethics-framework/australias-ai-ethics-principles>>

'CBA partners with global AI leader H2O.ai', *Commbank* (Web Page, 8 November 2021) <<https://www.commbank.com.au/articles/newsroom/2021/11/CBA-partners-AI-leader.html#:~:text=We%20will%20be%20using%20our,as%20Amber%20Energy%20and%20CoGo.%E2%80%9D>>

'Data and AI: The next revolution', *Westpac IQ* (Web Page, 26 July 2021) <<https://westpaciq.westpac.com.au/Article/48825#:~:text=Launched%20in%20late%202019%2C%20the,any%20harm%20caused%20by%20AI>>

'OCC Working With Tech Firms on Credit Score Alternatives', *American Bankers Association* (Web Page, 25 June 2021) <<https://bankingjournal.aba.com/2021/06/occ-working-with-tech-firms-on-credit-score-alternatives/>>

Ringland, Emma, 'Ethics, diversity key as AI takes hold', *Westpac* (Web Page, 3 July 2019) <<https://www.westpac.com.au/news/making-news/2019/07/ethics-diversity-key-as-ai-takes-hold/>>

Townson, Sian, 'AI Can Make Bank Loans More Fair' *Harvard Business Review* (Web Page, 6 November 2020) <<https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair>>