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Mediating access: unpacking the role of algorithms in digital tenancy application technologies

Linda Przhedetsky

Faculty of Law, University of Technology, Sydney, Australia

ABSTRACT
Digital tenancy application technologies (DTATs) are becoming the dominant means through which renters in the private rental sector (PRS) apply for housing. These PropTech tools, which claim to streamline application processes to save renters and lessors time and effort, necessitate the collection of data. Though the collection of certain data – such as income and rental history – has long been a standard part of rental application processes, DTATs now facilitate the collection of additional data including social media activity, behavioural data, and more. Increasingly, DTATs offer the ability to 'make sense' of this data, evaluating applicants through the use of algorithms. Drawing on lessons from banking and insurance sectors, this article outlines how DTAT algorithms can reshape individuals' access to essential services delivered through competitive markets. It explains how algorithmic processes can introduce and exacerbate the unfair and unlawful treatment of renters, which can result in significant harms. To identify, redress, and prevent these harms, I argue that it is crucially important to use shared terminology to describe how DTATs are collecting and using data. This article introduces a framework for understanding how algorithms 'screen' and 'sort' applicants based on the data that is collected through DTATs. The process of 'sorting' is further broken down into three categories – 'scoring', 'rating', and 'ranking'. The article concludes by explaining how this framework can assist researchers and policymakers to identify, analyse and prevent harms that are catalysed, or exacerbated by DTATs.

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Digital technologies influence many aspects of how real estate is funded, designed, built, used, and maintained. The functions of such technologies and the industry that they have come to define are commonly referred to as 'PropTech' (Mattarocci & Scimone, 2022). Since the 1980s, the PropTech industry has developed against a backdrop of housing financialisation and 'platform capitalism' (Langley & Leyshon, 2017), radically reshaping real estate markets andthe businesses that operate within them. Housing financialisation has been driven by a growth in real estate companies and investment trusts that typically

CONTACT Linda Przhedetsky linda.przhedetsky@uts.edu.au Faculty of Law, Level 16, UTS Central (Building 2) Broadway, Ultimo, NSW 2007, Australia

purchase housing stock as part of a long-term investment strategy (Wijburg et al., 2018). By detaching the 'material dwelling from the subjective lived experience of habituation, into digital data to facilitate new types of capital circulation and accumulation' (Rogers, 2017, p. 137), the home has been transformed into an asset from which rent can be sought. Consequently, housing has increasingly become conceptualised as a commodity from which commercial value can be extracted, rather than as a social good. The extractive logics that underpin housing financialisation mirror those that underpin platform capitalism, which transplants value from the means of production and instead ascribes value to information (Srnicek, 2017), which, in the context of this article refers to renters' data.

This discussion focuses on PropTech businesses that operate within the private rental sector (PRS): specifically, the digital platforms that mediate people's access to formal housing arrangements, which are typically secured through written contracts and guaranteed through security deposits (or rental bonds). This article focuses on a subset of PropTech tools – digital tenancy application technologies (DTATs) that are typically marketed to real estate agents and property managers who look after properties owned by 'Mom-and-Pop' landlords (as opposed to those owned by institutional investors). The DTATs discussed in this article facilitate commercial relationships in a multi-sided rental market and in doing so, 'actively compel, construct and configure the way that users, data and commodities are on the move' (Hill, 2021, p. 569). In this way, DTATs add an additional structural layer that shapes how real estate is accessed and organised.

This article represents an attempt to describe and critique how algorithmic logics within DTATs can produce unfair and unlawful outcomes for applicants. The first section of the article situates DTATs within the broader landscape of PropTech, positioning them as intermediaries between lessors (landlords, real estate agents or property managers) and renters. The second section discusses the goals of tenant selection and the challenges of digitalising the tenant selection process without appropriate regulatory safeguards. The third section problematises algorithmic logics embedded within DTATs which 'make sense' of data to evaluate rental applicants. Here, I explain how 'classification situations' that shape life chances (Fourcade & Healy, 2017) are created using opaque algorithmic techniques, many of which are based on practices drawn from finance and insurance industries. The fourth section introduces a classificatory framework that differentiates between 'screening' and 'sorting' (with the latter being further broken down into 'scoring', 'rating', and 'ranking'). This framework is offered to help identify, document, and explain how harms are occurring as a result of DTAT use in the PRS. The fifth and final section critiques the language of tech-solutionism that permeates PropTech marketing and promotes DTATs as tools to minimise risk and maximise efficiency, while obscuring their shortcomings. The article concludes by positioning the proposed framework as a practical tool to begin accurately identifying, understanding, overcoming challenges that result from, or are exacerbated by DTATs.

I note that the use of DTATs and other emerging technologies in the PRS warrants further exploration. This article focuses primarily on examples from Western nations, where research on DTATs is most extensive. Many of the examples referenced are drawn from Australia, the US, and the UK, where DTAT use is widespread, and where (very limited) research into these technologies is currently concentrated. The identified examples are illustrative of issues that transcend local contexts, and highlight practices that may harm people in jurisdictions where such technologies are largely unregulated, or where existing regulation lacks enforcement. These examples are not designed to paint a comprehensive picture of every harmful practice resulting from DTATs but rather, are intended to serve as a prompt for researchers and policymakers to consider current and potential impacts of DTATs, especially as these technologies continue to become more widespread, more sophisticated, and more prevalent in housing markets around the world.

Situating digital tenancy application technologies in the PropTech landscape

Within the PropTech industry, there are ample examples of novel datasets that are collected or generated for commercial gain: from pageviews of online property advertisements to share house expense records, to data collected and generated about prospective tenants – the subject of this article. As datafication reshapes and creates new social and economic relationships (Landau-Ward & Porter, 2019), those without, or with fewer existing assets (both data and property) are less likely to be data holders and are more likely to have data held *about* them. These dynamics can exacerbate existing social and economic inequalities. For example, in 2023 Australian DTAT 2Apply offered to increase applicants' privacy protections for the cost of AUD $20 (Malo & Dib, 2023). Of course, this is not a cost that everyone can afford, and those unable to pay the monetary cost end up paying by handing over data, or missing out on the service. Though it's sometimes argued that consumers hand data over to businesses because 'masses of people – naively or unwittingly – trust their personal information to corporate platforms' (Van Dijck, 2014, p. 197), I contend that naivety, unwittingness, and trust are not prerequisites for data collection by DTATs. Instead, I suggest that information is taken by businesses, or reluctantly offered by consumers who do not necessarily provide genuine consent (CHOICE, 2023, p. 9). The proliferation of DTATs in the rental sector means that consumers are increasingly compelled to create digital applications or profiles that expose them to extractive data practices and classificatory logics, while being required to pay (in the form of money, data or time) to access housing – an essential service.

The extraction, transmission, transformation, storage and organisation of data in the PropTech sector is typically mediated by digital platforms that operate with commercial imperatives. Sadowski argues that a successful platform is one that becomes 'a (necessary) intermediary' in the market, and then shapes the market in turn (2020, p. 568). While it appears that DTATs are successfully entrenching themselves as intermediaries within the PRS, the opacity of the industry and the nascency of this research field means that there are limited data available to understand levels of uptake. Available research shows that most landlords appear to screen prospective tenants in the US (Consumer Financial Protection Bureau, 2022), and that 41% of Australian renters have felt pressured to use a third-party platform to apply for a rental (CHOICE, 2023).

As intermediaries, PropTech businesses not only exercise economic control, but also have profound social and political effects. The social impact of platforms is summarised by Andersson Schwartz, who explains that platforms influence how social relationships operate: 'as relationships are turned into material infrastructure, existing arrangements are lent a degree of immutability and traceability, rendering what previously would have been informal exchanges into much more formalized rules of engagement' (2017, p. 377). DTATs using algorithms to analyse the contents of tenancy applications to evaluate prospective tenants is an example of this. Prior to the use of DTATs, rental applications were interpreted by lessors according to their values, preferences and interactions with tenants. Now it is possible for many elements of the application process to be entirely automated, leaving less room for interpersonal interactions to influence outcomes. Though most DTATs prompt a person to make the final decision that determines who is offered the tenancy (Short et al., 2008),[1] algorithms (which in essence, act as decision-support systems that provide information which may aid a human in making the final decision) formalise a significant portion of the assessment process by systematically evaluating applicants' suitability.

Tenant selection in the age of digital tenancy application technologies

When processing applications of prospective tenants, the role of a lessor can be described as 'assessing the risk of a potential tenant and choosing the best possible tenant for the rental property' (Bate, 2020, p. 592). In an Australian context, assessing the 'risk' of prospective tenants generally refers to evaluating applicants to determine whether they demonstrate an 'ability to pay' and an 'ability to care' for the property (Short et al., 2008, p. 2). This aligns with the findings of Dunn and Grabchuk who explain that lessors in the US use basic criteria that 'usually fall along the twin axes of financial suitability and behavioural suitability' to identify a 'good tenant' (2010, p. 322).

When it comes to demonstrating their ability to accurately and reliably analyse applicants' abilities to pay and care for a property, DTATs' value propositions are typically tied to the quantity and range of data sources that they use ('Our background checks scan millions of records' [Smartmove, 2023]); the granularity of their analyses ('Gauging ethics, honesty, intelligence, attitudes, and beliefs, we develop a deeper and quantitative understanding of risk' [Pendo, n.d.]); the sophistication of their proprietary algorithms ('make informed decisions using scientifically valid and reliable metrics' [10ant Profiles, 2021]), or their ability to glean new insights from data ('[AI] Screening is more than just a credit score on the ability to pay – it's about the willingness to pay' [RealPage, n.d.]). In addition to having their financial data scrutinised to determine their ability to pay, rental applicants 'must also satisfy a series of inquiries into matters of character, lifestyle, and personal history', which allegedly inform their ability to care for a property (Dunn & Grabchuk, 2010, p. 319). Some DTATs purport to not only ascertain which applicants can pay and care for the property, but in instances where multiple applicants are deemed able to meet these criteria, offer a more granular assessment that claims to 'find the right tenants faster' (RealPage, n.d.). As DTATs become more sophisticated, greater quantities of data are being analysed with increased algorithmic precision to inform who should and shouldn't be granted access to rental housing.

So far, this article has outlined a range of challenges resulting from the collection and use of information by DTATs. When discussing both procedural and substantive fairness in relation to DTATs, too little time has been spent discussing which information should be collected, and *how* it should be assessed. In the policy arena, these questions remain largely unanswered. There are, of course, legal limitations on the collection and use of data contained within privacy and data legislation, such as the EU's General Data Protection

Regulation (GDPR), or the *Privacy Act 1988* in Australia. Legislation on data and privacy varies considerably between jurisdictions, meaning that some of the examples highlighted in this paper would be unlawful in some jurisdictions, but not in others. Other laws of general application, including anti-discrimination law and consumer protection law also provide legal guardrails for how DTATs can use data. Increasingly, laws such as the EU's AI Act are conceptualising specific technologies as regulatory targets with a view to limiting how they can be applied in specific contexts. In some jurisdictions, there are also regulations specific to residential tenancy sectors, which dictate aspects of how renters' applications can be accepted and assessed (Short et al., 2008).

One issue in applying existing regulations to DTATs is that these regulations typically outline how information can be collected and used in ways that are legal – but don't necessarily outline how these processes can occur in ways that are considered fair, and align with societal expectations. Take for example, a DTAT that asks an Australian rental applicant to indicate whether they are receiving government benefits (Snug, 2023), and requests that the applicant's manager answers whether they consider the applicant to be a 'punctual, hard working, reliable and responsible' employee (Touma, 2022). If the applicant was penalised by the algorithm for indicating that they received government benefits, it is unlikely that they could seek redress through the application of anti-discrimination law, as welfare status is not a protected attribute under Australian legislation. Equally, if an applicant's employer provided a false assessment of the applicant that did not portray them favourably, it is unlikely that the applicant would be able to find out that this occurred, or seek to challenge the characterisation – legally or otherwise. This demonstrates that there is a gap between what is legal, and what might be considered appropriate in assessing an applicant. Some governmental efforts have been made to bridge this gap. In the United States, where DTATs are most prevalent and most technically advanced, the Department of Housing and Urban Development has issued guidance to private housing providers using criminal records to assess applicants, and in doing so, noted that algorithms can 'contain racial or other prohibited bias in their design' (McCain, 2022, p. 2). One of the key recommendations included in this guidance was that private housing providers 'should consider not using criminal history to screen tenants for housing' to reduce discriminatory effects (McCain, D. L., 2022, p. 8). In the Australian context, the New South Wales Department of Fair Trading issued guidance on the collection and use of personal information in tenancy applications (Fair Trading, n.d.). This guidance, aimed at industry, provides suggestions for how to assess applications 'fairly and on non-discriminatory grounds'. While the guidance suggests that 'agents, landlords and third party tenancy application platforms should explain why certain information is being collected and how it will be used to assess the person's suitability for the tenancy', it is important to note that this guidance is voluntary and does little to meaningfully incentivise DTAT providers to offer such disclosures, nor does it provide a clear framework for which information *should* be considered, and *how*.

In academic literature, So has made significant contributions in documenting how landlords assess information contained within tenant screening reports (So, 2023). So's findings demonstrate that some landlords maintained blanket screening policies, 'which means they den[ied] tenants with criminal or eviction records regardless of the outcome of the case' (2023, p. 1485) and tended to 'conflate the existence of the record with a negative outcome for the tenant … the presence of an eviction record was interpreted as evidence of an executed eviction' (So, 2023, p. 1498). Given these findings, So suggests regulating how certain information can be used. Specifically, the author suggests that 'landlords who want to assess tenants' eviction records should be obligated to check the details of eviction records and assess them accordingly' (So, 2023, p. 1501). Operationalising this would require DTATs to provide the option for lessors to check records and may require certain DTAT interfaces to be redesigned.

As more of the 'work' of tenant selection is 'done' by algorithms, it is increasingly important to consider how individuals and algorithms influence tenant selection through analytical techniques that 'make sense' of data.

'Making sense' of data

Classification systems can be conceptualised as a 'set of boxes (metaphorical or literal) into which things can be put to then do some kind of work – bureaucratic or knowledge production' (Bowker & Star, 1999, p. 10). Algorithmic systems *automate* these classification processes which, in the context of DTATs, are used to organise rental applicants based on their data (performing a bureaucratic function) or interpret and evaluate applicants (producing knowledge about them). Algorithmic classification systems may remain consistent (in the form of expert systems)[2] or change over time, evolving their classification logics through processes such as machine learning.

A range of literature elucidates how, by 'making sense' of data, algorithms influence, and in some cases, determine, people's social, political, and economic opportunities. Amoore describes how machine learning algorithms enforce 'regimes of recognition' (2020), Citron and Pasquale describe the 'scored society' in which algorithms are used to assign reputational metrics (2014), while Fourcade and Healy conceptualise algorithms as creating 'classification situations that shape life chances' (2013, p. 559). Fourcade and Healy's work is particularly useful in understanding how algorithms enact systems of moral classification that determine who can access certain opportunities (in the context of this article, rental housing), and who gets their 'just deserts' (2017, p. 2). Algorithmic classification systems are marketed with the promise of helping lessors find a 'good tenant' and picking up on 'subtle warning signs' that a human is likely to miss (Cubbi, 2023). In other words, algorithms are promoted as tools that can do the work of detecting traces of the undesirable, and identifying instances of moral trespass. The language of moral classification can be easily located in a range of DTATs: for example, Australian company 10ant Profiles uses a 15-question questionnaire to produce a 'Tenant Safety' report which the company claims can provide 'insight[s] into how you [the tenant] tend to think and act' (10Ant Profiles, 2021). The DTAT provides an overall 'Safety Score' from 0–100 (shown on a scale), alongside percentages and colour ratings that are used to evaluate the candidate's 'Care' and 'Accomodation'.

DTATs take data inputs and use these to produce outputs based on predetermined logics. For example, at the time of writing it appears that Snug, an Australian DTAT, allows property managers or landlords to set preferences such as 'start date, rent and term' which determine how applicants' data is weighted to produce a 'Match Score' out of 100 (Snug, 2023). Other tools appear to rely on more detailed pattern recognition techniques that first identify patterns, then give them meaning. An example of this is Certn's technology, which claims to use algorithms to identify social media red flags by analysing the 'content of images, text content of written posts, and metadata' (Certn, 2023). This North American DTAT claims to screen applicants' social media for categories such as 'political speech' and 'explicit/racy images'. Though the algorithmic model used by Certn is likely to have pre-defined criteria that determines what constitutes a 'red flag', it's unclear what training data was used to inform what fits into this category. Further, it is unclear whether the technology can differentiate between a genuine 'red flag', and a false positive. Because Certn interprets applicants' social media data according to predetermined logics that are invisible to applicants, it is impossible for prospective renters to know *how* this technology will 'make sense' of their data.

Finance, Insurance and Real Estate (FIRE) sectors harness algorithmic technologies to 'create, combine, monitor, move, store, send, analyse, and act on data of myriad types about people, processes, and places in the world' (Sadowski, 2022, p. 451). Leveraging algorithmic techniques to process Big Data, FIRE sectors have become adept at analysing novel data sources to evaluate individuals – for example, the financial industry's analysis of 'thin file' (those with little or no credit history) borrowers' digital footprints (Ciocănel et al., 2022). As the PropTech industry continues to draw on both algorithmic techniques and data sources from finance and insurance sectors, the interdependencies between these sectors are strengthened: nowadays, to appear competitive in the PRS, a person must also have a favourable financial identity. Wainwright illustrates how the UK's open banking API enables DTATs to analyse applicants' bank account data (2023). Although sharing this data is technically optional, renters are increasingly compelled to provide consent to be considered for housing (2023, p. 349). Migozzi shows that credit scoring is a well-established part of the tenant selection in South Africa (2020), while Schneider documents the use of credit reports in tenant selection within the United States (2020). Although Australian privacy law provides that real estate agents and landlords are not permitted to obtain consumer credit reports (and therefore, applicants are not required to provide them), there is evidence that lessors are still requesting that this information is provided as part of tenancy applications, further demonstrating the enmeshment of finance and real estate sectors (CHOICE, 2023).

In finance and insurance industries, risk determination practices are typically underpinned by actuarial science techniques. These are often subject to regulation, for example, scrutiny by specialist credit committees (Wainwright, 2023). A key challenge is that new analytical techniques and novel datasets (for example, social media data or information about hobbies) factor into some DTATs' assessments of applicants, yet their use receives considerably less scrutiny than similar practices in financial and insurance industries.[3] When investigating the US PropTech sector, The Consumer Financial Protection Bureau noted that 'common practices in financial services credit risk operations, such as documented model validation and risk management, do not appear to be prevalent in risk modelling' (2022, p. 3). This means that not only are certain data collection and analysis practices used by DTATs ethically questionable, but the algorithms underpinning them may also lack efficacy. Wainwright's research in the UK documents similar issues and adds that smaller PropTech companies 'tend to use their own ideas, introducing more variation in how the data is used in their algorithms', which suggests that algorithmic logics underpinning DTATs may vary considerably (2023, p. 352).

As discussed earlier, 'making sense' of data is a process that involves analysis, interpretation, and evaluation of data according to business logics embedded within algorithmic systems. Algorithmic classification systems often appear ‘neat and definitive despite the messy sources of information feeding them, creating an artificial orderliness with rankings that can easily pass as legitimate given they are rooted in an individual’s doing’ (Ciocānel et al., 2022, p. 20). This false veneer of neutrality functions to mask the fact that technologies are constructed according to their creators’ economic and political interests and ideologies (Boeing et al., 2021). Recent contributions by scholars including Schneider (2020), Reosti (2020) and others have highlighted how DTATs can and do lead to unfair, and discriminatory outcomes based on the algorithmic logics encoded within them, often replicating and reinforcing the exclusionary logics, social and spatial hierarchies that are already present in broader society (Fields, 2019, p. 580). Humber (2023) illustrates how DTATs can replicate existing inequalities in the form of algorithmic redlining, when the *data* they process (for example, criminal records) reflects existing discriminatory practices and structural inequalities. The combination of algorithms being marketed as powerful, objective tools that can predict future outcomes and the range of well-documented issues with DTATs makes for a particularly dangerous mix.

In competitive rental markets where there are multiple applicants for most rental properties, there are few commercial incentives for lessors using DTATs to challenge the output of systems they have already invested time and money in setting up, unless their system’s recommendations were significantly misaligned with their own evaluations of tenants. So’s research into landlords using DTATs showed that they exhibited automation bias (the tendency for humans to favour suggestions produced by algorithms over contradictory information made without automated tools) and, rather than using additional available information to make decisions about tenants, tended to rely on the risk scores produced by DTATs to evaluate applicants (So, 2023). Rosen et al. have found that when landlords lack ‘the information they think they need to make a [tenant] selection, or are banned from directly using such information, they put more emphasis on algorithmic proxies such as credit score or eviction history’ (2021, p. 790). These studies demonstrate that some lessors rely heavily on algorithmic outputs in the tenant selection process, often without querying how or why a particular output was produced. Here, it’s equally important to note that not all lessors place full confidence in DTATs: Beer et al. make a valuable contribution in documenting automation hesitancy towards the implementation and use of algorithms in the UK’s PRS (2023).

For people navigating a competitive PRS, there are few (if any) opportunities to challenge the outputs of DTATs. Renters won’t always be shown how they are evaluated by DTATs, and in instances where they are provided with a score or rating, it ‘may not be clear to them individually why they were rejected, or deprioritised in an application’ (Wainwright, 2023, p. 351). If renters ask lessors why they were rejected, lessors may not want to, or be able to explain how the DTAT used evaluated applicants, or to what extent the DTAT’s output influenced tenant selection. This can make discrimination and unfair treatment harder to detect. As Reosti explains, lessors in competitive markets are often granted ‘plausible deniability’ as discriminatory or unfair ‘tenant selection decisions can be credibly explained away in reference to the existence of other applicants who are better qualified on non-discriminatory dimensions like income or credit score’ (2020, p. 627).[4] Of course, applicants may consider accessing redress (legally or otherwise), but this is difficult (in part, due to the lack of information available about how DTAT algorithms evaluate renters), time-consuming, and is unlikely to assist them in securing rental housing, as any property they have been rejected for on the basis of a discriminatory or unfair assessment is likely to have already been leased to another applicant.

As governments, civil-society organisations, researchers, and advocates try to unpack what *does*, and what *should* constitute legal and fair tenant selection, it becomes increasingly important to discuss tenant selection processes using a shared language. By clearly identifying the processes by which applicants are evaluated, we can begin to understand what measures can be taken to provide applicants with redress where harms have occurred, and put in place solutions to prevent future harms resulting from DTATs. The next section of this article offers a framework to help describe and differentiate between screening and sorting functions employed by DTATs.

Unpacking screening and sorting practices: a proposed framework

Discussions of DTATs in commercial, policy and government contexts use a range of terms to describe algorithmic functions. Terms such as 'screening', 'scoring', and 'sorting' are used interchangeably despite referring to different processes. Similar challenges are present in academic literature. Wainwright points to 'two main mechanisms at work when using data to sort potential tenants' in the UK PRS, delineating between 'binary sorting and ranking' (2023, p. 350). Nethercote describes how PropTech technologies 'score, sort and stratify renters' (2023, p. 2), while Ferreri & Sanyal use the term 'screening' to refer to a range of evaluation practices (2022).

As discussed in this article, there is ample evidence of harms that result from the collection and use of data through DTATs. To provide individuals with redress and prevent future harms, we must therefore be able to identify, document, and explain how harms are occurring. To do so, it is necessary to use a shared language to describe the algorithmic processes at work. This section provides a simplified framework that is offered as a tool to better differentiate between algorithmic processes in DTATs. First, I distinguish between 'screening' and 'sorting', before outlining differences in sorting processes embedded within DTATs. Though it is important to emphasise that 'screening' and 'sorting' can be different processes, they may be indistinguishable from an applicant's perspective. The separation of the two processes is emphasised for the purposes of identifying precisely *when* and *how* consumer harms occur within tenancy application systems, and to effectively identify strategies for prevention. It is therefore hoped that this framework will provide an opportunity for researchers, policymakers, and regulators to better describe the processes embedded within DTATs, and specifically, to identify how data is being used to evaluate rental applicants. In presenting this framework, I note that it *does not* speak to specific algorithmic methods (for example, machine learning, natural language processing) or models which may be used as part of DTATs. Further research into the use of different algorithmic methods in DTATs may further inform or expand upon the framework presented.

Screening

Sometimes referred to as 'vetting' or 'pre-screening', screening is a process carried out by some, but not all DTATs – sometimes separately, or in combination with 'sorting' functions. I propose that screening should be considered:

- the automated search for specific attributes relating to an individual (for example: does the individual's application contain evidence of employment? Does the individual's profile match with an eviction record contained within a database?), or
- the automated process of determining whether an individual meets a pre-determined threshold (for example: is the individual's stated income sufficiently high, so that they would not be spending more than 30% of their earnings on rent if approved for this property?).

An example of a screening function can be found in US-based SparkRental (n.d.). This DTAT uses data matching, which identifies whether a rental applicant can be linked to 'Most Wanted List' records, 'National Sex Offender Registry' records, and more. Once the algorithm has scanned SparkRental's databases for relevant records, the DTAT displays whether matches have been found (indicating the presence or absence of the attribute), and the number of records that have been identified.

The presence or absence of these attributes can be used to filter out 'unsuitable' candidates, creating a smaller pool of applicants. This pool may then be 'sorted' prior to being displayed to the lessor. An example of this dual process can be found in US-based Tenant Turner, which offers a 'Fair Housing Act-compliant pre-screening' that eliminates 'unsuitable' candidates, before applying sorting techniques 'only on qualified leads' (2023). It is important to note that screening can be the chief automated process performed by DTATs, used to create a list of applicants who meet certain criteria without producing further analysis to differentiate between applicants. An example of this is Realestate.com.au's Tenant Check, which verifies renters' identities and determines whether the applicants are listed on Equifax's National Tenancy Database, which contains information about tenancy agreements that were breached or terminated by renters around Australia (2023).

Wainwright documents how affordability checks are conducted in the UK's PRS to determine whether renters can meet monthly rental payments: they 'either meet the criteria, or they do not' (2023, p. 350). In this example, screening is used to determine whether a renter can meet a pre-determined threshold, which is based on a rent:income ratio. Some DTATs may enable users to set multiple thresholds across different criteria (for example, income, number of residents on the application, length of lease) which may be used to narrow the pool further. Once screening has occurred, the design of DTATs may be such that lessors can pick from a shortlist of applicants, apply various filters to order candidates' profiles, or refer to outputs from 'sorting' processes, if these have been conducted.

Sorting: scoring, rating, and ranking

In instances where there are multiple suitable applicants for a property, applications may be 'sorted' to help determine who the property will ultimately be offered to. The term 'sorting' is used to refer to automated processes through which data is analysed and weighted to assess an application according to algorithmic logics. Sorting tends to involve the analysis of many datapoints to produce an overall evaluation of a rental applicant, which, as described throughout this article – can involve opaque, sometimes controversial logics.

I note that some DTATs allow filters to be applied by the lessor – for example, a filter to only show applicants that have not listed a pet as part of their application, or a filter that ranks applications according to the weekly rent offered (most-least expensive). Filters that organise information which has not been transformed algorithmically (for example, ordering applicants according to when applications were received or organising applications alphabetically) are excluded from this framework, whereas filters that organise algorithmic outputs (for example, organising applicants according to an algorithmically generated 'Match Score' [Snug, 2023]) are in scope.

I conceive of the sorting process as involving the evaluation or organisation of applications. To better describe how these processes operate, I differentiate between sorting functions as follows:

- Scoring is the evaluation of applications represented numerically, often as a fraction or percentage,
- Rating is the evaluation of applications in the form of a colour, letter, symbol or otherwise. Ratings are often represented on a scale, or place the applicant within a range, and
- Ranking is the organisation of applications in a hierarchical order based on algorithmic output.

These processes may be used separately, or in conjunction with one another. SmartMove is a North American DTAT that provides a numerical 'Resident Score' in evaluating a prospective tenant (2023). In addition to providing a score between 350 and 850, SmartMove uses colour ratings to provide an additional way for lessors to interpret how candidates have been evaluated. A bright green colour rating is associated with a high score, an orange rating a mid-range score, and a red rating with a low score. Canadian DTAT Pendo also provides an overall score /100, and uses words ('low', 'average', 'high') to rate a candidate's likelihood to correspond with desirable behavioural attributes such as 'honesty', 'credibility' and 'stability' (2023). It is worth noting that no evidence has been provided to suggest that these assessments are based on causal inferences.

The 'ranking' of candidates is demonstrated by Australian DTAT Snug, which show that lessors can use filters to rank applicants according to algorithmically generated 'Match Scores', which are represented as a number /100 (2023). As evidenced by these examples, DTATs employing sorting processes tend to use a combination of scores, ratings, or rankings.

Catalysing, exacerbating, and scaling problems

Like other PropTech businesses, DTATs commonly position themselves as offering technological solutions that solve a range of problems in the real estate market (Shaw, 2020). To lessors, these technologies are marketed as cost-effective tools that can improve efficiency, minimise risk, reduce costly adverse outcomes by leveraging data to analyse individuals' histories, with some DTATs even claiming to predict tenants' future behaviour (Consumer Financial Protection Bureau, 2022; Przhedetsky, 2023). DTATs operate on the assumption that once screening or sorting techniques have been applied to applicants' data, the process of selecting a tenant will be made simpler for lessors.

In Fields' discussion of the 'automated landlord', a concept used to describe the management and mediation of tenants and properties through new technologies, the author notes that DTATs and other rental technologies are also a 'response to the obstacle of distance inherent in attempting to centrally operate large and dispersed property portfolios' (2022, p. 171). The formulaic nature of DTATs allows them to act as 'obligatory passage points for social exchange' (Hendrikse et al., 2022, p. 59) – through which information can pass, but only if it fits a certain mould. To renters, these technologies are marketed as offering the chance to 'put their best foot forward' (Snug, 2023), 'prove you're the perfect fit' and 'give yourself the best chance of standing out' (Realestate.com.au, 2023). Renters are promised the opportunity to articulate (and perhaps, refurbish) their image so that their application is 'seen' by algorithms and human assessors to meet often ill-defined, or invisible criteria, and to appear superior when compared to others' applications. In curating the presentation of their digital identities, renters make guesses as to which versions of themselves would be desirable and worthy of selection. Though some renters may succeed in understanding which data should be included or modified for them to be viewed as a worthy applicant – there are some factors that, if reported honestly, may disadvantage applicants' chances. These may include protected attributes including gender, age, and ethnicity (see, for example: National Consumer Law Centre, 2022; Rosen et al., 2021) or factors that are not formally protected under anti-discrimination legislation such as welfare status, income, and pet ownership. Indeed, many of these factors are not possible – or desirable – for renters to change, and thus, the promise of improving how one may be perceived as a prospective renter may be offered under false pretences. The cost to obtain a background check, the risk of inaccurate information being pulled from databases, and the technical challenges of using systems that may be hard to navigate for people who are not technologically literate or deliberately lack an online presence may pose additional challenges for some renters as they attempt to present a desirable digital image (Przhedetsky, 2023). Further, the formulaic ways that DTATs structure application processes (for example, providing highly specific, predetermined questions that applicants need to answer) may mean that lessors might not be able to identify tenants that could be seen as desirable in other ways. For example, a lessor seeking a long-term tenant may overlook an applicant whose profile was linked with a criminal record in a DTAT's screening process, or who scored poorly on 'honesty' in a DTAT's sorting process. Whether or not the applicant was offered the opportunity to provide any context (for example, to explain that their criminal record was a minor offence committed many years ago, point out that they don't have a recent rental history in this country in because they have just returned from living abroad, or to indicate that they were seeking a home that they would be able to live in for an extended period of time), the DTAT's interface may not be conducive to enabling applicants to effectively challenge how they have been classified, or to encourage lessors to look beyond the DTAT's outputs.

The Proptech industry's technological solutionism (Morozov, 2013) can obscure the problems that these technologies create and exacerbate. This article deliberately problematises the role of platforms in mediating access to housing in the PRS and takes issue with the opaque, and at times harmful classificatory logics that are used to determine who has access to housing (Landau-Ward & Porter, 2019) by identifying how screening and sorting processes can complicate access to this essential service. Fields and Rogers explain that ‘housing is a crucial vector of social and spatial inequality and thus of contentious power dynamics’ and call for the impact of digital technologies in residential real estate to be studied closely (2021, p. 72). Through this article I have answered their call, contributing an analysis of the organising functions of tenancy application technologies, and critiquing how these tools ‘make sense’ of data through algorithms. In doing so, it is important to note that I do not conceive of all PropTech technologies as inherently negative additions to the real estate market. While this article focuses on harms, I wholeheartedly agree with Fields, who suggests that ‘we must look to movements that are using platforms and other tools of the Tech Boom 2.0 to support long-standing struggles for housing justice’ (Fields, 2019). In saying this, it is critical to acknowledge that current market structures and regulatory frameworks enable, if not invite, PropTech companies to exploit people’s data, and mediate access to housing in ways that exacerbate and further entrench inequality. To achieve genuinely positive outcomes for tenants we mustn’t passively accept the PropTech industry’s definitions of problems, as this only leads us to accept the industry’s logics of solution. While a detailed assessment of the potential benefits of PropTech is out of the scope of this paper, I note that with appropriate regulatory guardrails, commercial incentives, and importantly, consultation with end users and people with lived experience of renting, the use of screening and sorting processes in DTATs may, in the right circumstances, present opportunities to improve upon the status quo.

Conclusion

Though there are indeed possibilities for PropTech to be harnessed in ways to promote fair and lawful practices in the PRS, this article demonstrates a range of harms that can result from DTATs in markets without appropriate regulation or enforcement. Further research is needed to understand the differences between screening and sorting processes to evaluate how they are currently used, and to understand how they can be implemented and regulated to achieve fair and lawful outcomes for renters. I hypothesise that screening processes (although they can be compromised through the inclusion of inaccurate or biased data) could be more easily and quickly improved through regulatory intervention than sorting processes. For example, improved screening processes may be achieved by limiting which information can be screened for, which data sources are able to be used in a screening process, and which thresholds can be set. I also anticipate that sorting practices, which typically involve DTATs using more diverse datasets and more complex, less transparent logics, currently pose the most significant risks to renters applying for properties. Examples of sorting practices contained within this article demonstrate that dubious (and potentially inaccurate) analytical techniques are being used to predict renters’ future behaviour, and in doing so, determine their ‘life chances’ (Fourcade & Healy, 2013).

To understand the implications of sorting practices, test the applicability and usefulness of regulatory protections for renters, and identify regulatory gaps, we must first be able to understand what’s happening within DTATs. The framework presented here, though it does not allow us to peer into the inner workings of DTAT algorithms, provides a tool for advancing the conversation.

Notes

1. As Short et al. note, real estate agents and property managers will regularly shortlist candidates before making recommendations to landlords, who typically make the final decision to determine who is offered the property (2008, p. 37).
2. Expert systems are rule-based systems that can solve complex problems. These systems often use deductive reasoning and rely on if–then rules to reach a conclusion. An example of an expert system is a decision tree.
3. Although, as Bednarz and Przhedetsky (2023) suggest, financial sectors in US, UK, EU and Australia lack adequate regulation when it comes to protecting consumers from harms resulting from the unfair or unlawful use of information from novel datasets.
4. Credit scores are calculated algorithmically, and it is important to note that there are credit disparities between racial and ethnic groups (Boshart, 2022).

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Notes on contributor

Linda Przhedetsky is an interdisciplinary researcher and doctoral candidate at the University of Technology, Sydney [email: linda.przhedetsky@gmail.com].

ORCID

Linda Przhedetsky http://orcid.org/0000-0003-1798-1100

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