Paths to Social Licence for Tracking-data Analytics

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Abstract

While tracking-data analytics can be a goldmine for institutions and companies, the inherent privacy concerns also form a legal, ethical and social minefield. We present a study that seeks to understand the extent and circumstances under which tracking-data analytics is undertaken with social licence — that is, with broad community acceptance beyond formal compliance with legal requirements. Taking a University campus environment as a case, we enquire about the social licence for Wi-Fi-based tracking-data analytics. Staff and student participants answered a questionnaire presenting hypothetical scenarios involving Wi-Fi tracking for university research and services. Our results present a Bayesian logistic mixed-effects regression of acceptability judgements as a function of participant ratings on 11 privacy dimensions. Results show widespread acceptance of tracking-data analytics on campus and suggest that trust, individual benefit, data sensitivity, risk of harm and institutional respect for privacy are the most predictive factors determining this acceptance judgement.

Keywords: Social Licence, Tracking data, Acceptability, University research, Wi-Fi, location data

Introduction

The increased simplicity of acquiring tracking data (spatio-temporal data attached to an identifiable object or person), and their immense utility for logistics, traffic and space management, human resource management and reporting, and advertising has turned tracking-data analytics into a revenue goldmine. Yet, the inherent privacy concerns of tracking data turn them equally into a minefield.

One source for tracking data are Wi-Fi networks. Campus-based universities, shopping malls, and hospitals are examples of complex, built environments with varied stakeholders and complex logistical issues that, on one hand, operate such Wi-Fi networks, and on the other need data-driven support for efficient operations. The realisation that tracking data contain information about staff attendance, can support health and safety reporting and compliance monitoring, and inform space-use optimisation leads to an increased interest in active tracking technology deployments.

On university campuses, such data are often applied to the optimization of campus management, operations, and university services. While, these uses are often legally covered by the Wi-Fi user agreements, a failure to ensure that participants broadly accept their operation can cause negative media attention and attitudes towards the university¹⁻³. Further, these data are also of interest for academic research from a more fundamental perspective of advancing knowledge about the applications and limits of tracking data in a variety of domains. This includes research into privacy protection^{4,5} and obfuscation^{6,7}, data cleaning and interpolation^{8,9}, pattern detection and prediction, contact tracing¹⁰, and the integration of tracking-data with social media sentiments¹¹ or with student or staff performance¹². The use of the Wi-Fi tracking data for research purposes may not be covered in Wi-Fi user agreements, and may require additional informed consent. Wi-Fi users — the whole campus community — may feel uncomfortable with the topics, methodologies, or potential applications of some research and might thus resist having their data contribute towards them. On the other hand, many on campus might benefit from

more permissive use of such data through the provision of better university services and management, greater research opportunities for graduate students, and more diffuse public benefits at large. The above affairs illustrate the importance of securing the acceptance of a university community for the tracking-data analytics operations of a university. Yet, while the legal and ethical issues about the collection and processing of these potentially privacy-encroaching technologies has received much attention, little work has empirically considered the community perception and acceptance of personal tracking in this context.

The present study seeks to understand to what extent and under what circumstances tracking-data analytics is undertaken under a *social licence* — i.e., with broad community acceptance beyond formal compliance with legal requirements¹³. Understanding the acceptance by Wi-Fi users may help (a) academics to understand sensitivities and limits in advance, (b) ethics boards with formulating policies and guidelines, (c) university governance with a realistic evaluation of user sentiments, and (d) with a broader public debate on acceptable and unacceptable use of tracking data.

Participants in our study were exposed to a questionnaire presenting hypothetical scenarios depicting the use of Wi-Fi tracking data in research and support services at the University of Melbourne, and rated these scenarios on 11 privacy dimensions that were distilled from a literature review and from a workshop of university stakeholders from a variety of disciplinary, professional and other backgrounds (see the supplementary materials and Table S4 for an in-depth description of how we derived these 11 dimensions). After making these ratings, participants indicated whether each scenario was an “acceptable” use of university tracking data.

Results show general acceptance of university research and service projects that use Wi-Fi tracking data. The results also suggest that community trust of the sponsoring institution, beliefs about their respect for people’s privacy, the individual benefit conferred upon participants, the risk of harm of the project, and the sensitivity of the data being collected are the most important factors predicting this acceptance. Further, we build a predictive model to allow administrators, ethics boards, and other

decision-makers to foreshadow the level of community acceptance for new projects to assist their decision-making.

Background

Current wireless communication infrastructure and technology in managed environments such as university campuses, shopping malls and downtown areas allows the collection of tracking data of its users^{14,15}. The operators of the infrastructure will use this data for the optimization of their services, but other parties have an interest in this data as well, and some of the possible uses might be accepted by the users as useful, legitimate, or desirable. Yet, as with any technological advancement, social, ethical, and legal issues surround the data use. While infrastructure operators often focus only on satisfying the legal requirements that underlie operations, recent scholarship has emphasised the importance of going beyond this minimal threshold to technology deployment, and secure a broader basis for community acceptance

This notion — termed ‘*social licence to operate*’ — while developed primarily in the corporate social responsibility literature to describe the support and acceptance within the community of private companies’ operations (particularly mining companies), has recently gained traction in the context of large-scale personal data collection and analysis. There are a number of examples of recent controversies in the healthcare sector that exemplify the degree to which a failure to secure social licence for research initiatives can undermine project success; e.g., MyHealthRecord in Australia and Care.data in the UK¹⁶. Such failures to secure social licence, however, are not limited to the healthcare sector. Indeed, the release of information about the use of Wi-Fi and other big data in learning analytics in Australian universities has been similarly controversial and received backlash from students, regulators and the media^{2,17,18,1}. Such controversies have also occurred in US universities^{3,19}, and may cause negative media attention and attitudes towards institutions, as well as negatively affect the quality of the data collected through reduced compliance or cooperation. These examples illustrate the importance of

building social licence and trust amongst the community in a university and education setting if the potential benefits of use of Wi-Fi tracking data are to be realised in the future.

Extensive literature covers the ethically normative requirements for using big data in a variety of contexts^{20,21}, including in universities²². However, most work in relation to social licence focuses on the legal (i.e., what can entities legally do) and normative frameworks (i.e., what entities should do). However, little work has considered the social licence for big data usage from an empirical or descriptive perspective. While there has recently been an increase in this empirical work, it has generally been limited to the social licence for big data usage in governmental services or the mining industry^{21,23–25}. Here, we complement this gap by focusing on the quantitative analysis of the social licence for data use in research, in the context of data collected and analysed at Universities.

The aim of the present research is to understand the factors which affect the social licence for the use of Wi-Fi location data for research and university services. We argue that Universities are a particularly interesting environment to study from the perspective of social licence. The use of Wi-Fi location data in university research and services presents both great opportunities, but also risks. This data can be used to greatly benefit the community, by providing the ability to quickly conduct cutting-edge research with real and varied populations, the benefits of which to the community may be immense. In addition to legal requirements, institutional research ethics frameworks also govern Universities, providing extra oversight for data use. There is also a high level of collegiality amongst staff and students. For a productive and flourishing University community, it is crucial that this confidence is not undermined. Trust and confidence are particularly important because in many University institutions, individuals are a ‘captive’ population; individuals need to use the Wi-Fi network to effectively conduct their work and studies. As such, an individual’s ‘freedom’ to opt-out is fundamentally compromised. For this reason, it is vital to ensure protections are in place for stakeholder privacy, security and risk of harm and it is equally crucial to ensure social licence for trustworthy Wi-Fi location data use before implementation on campus.

138 To work towards a more nuanced understanding of the parameters of a social licence for the
139 research use of Wi-Fi data, in this paper we specifically address two research questions: first, which
140 scenarios for Wi-Fi location tracking do university community stakeholders find acceptable?; and
141 second, what are the factors within those scenarios that can predict this acceptability? From these
142 findings, we generalise predictive factors of community acceptability of new proposals for the collection
143 of university Wi-Fi location data. Our study has been conducted at the University of Melbourne, a
144 major, multicultural, public university in Australia.

Results

Acceptance and perception of tracking-data analytics on university campus

After reading scenarios that depicted the use of tracking-data analytics (summarised in Table 1) participants rated them on 11 privacy dimensions (summarised in Table 2) before making a binary judgement whether the use of tracking-data analytics in each scenario was acceptable. Figure 1 shows the proportion of participants that labelled each scenario as acceptable. The mean acceptance proportion among the scenarios was 0.715 ($SD = 0.111$). Figures S1 and S2 show participants’ perceptions of each of the scenarios in relation to each of the 11 privacy dimensions.

Figure 1. Participant perception of scenario acceptability. The proportion of ‘acceptable’ judgements for each scenario. The sample size for each scenario is listed at the base of the bar chart. Error bars represent standard errors of the mean.

Predicting acceptance of tracking-data analytics on university campus

Descriptive / Explanatory Model

Bayesian mixed effects logistic regression was used to predict participants’ acceptability judgements as an additive function of their privacy dimension judgements. Two candidate models were estimated: one which included one parameter for each privacy dimension, and one which also included some *a priori* interaction parameters between privacy dimensions (listed in table S1).

Model selection was conducted via Pareto-smoothed importance sampling leave-one-out cross validation to maximise the out-of-sample predictive accuracy of the model^{26,27} and the model with the

highest expected log predictive density (ELPD) was preferred. On this basis, the model without interactions (ELPD = -345.22, $SE = 17.54$) was preferred to the model with interactions (ELPD = -349.66, $SE = 18.80$). The preferred model had a Nakagawa conditional R^2 of 0.454 ($SE = 0.034$), indicating that 45.6% of the variance in the data was explained by the random and fixed predictor variables, and a Nakagawa marginal R^2 of 0.398 ($SE = 0.024$) indicating that 39.8% of the variance in the data is explained by the fixed predictor variables, i.e., the privacy dimension ratings²⁸.

Figure 2. Fixed effect posterior distributions from the preferred model. Point estimates (dots) are posterior modes and intervals are 89% highest density intervals (lines). Parameters for which a practically significant effect was inferred have interval lines coloured black. The region of practical equivalence is shown between the dotted vertical lines. Practically significant effects were inferred when the entire 89% highest density interval fell outside the region of practical equivalence.

Posterior estimates of all fixed model parameters are shown in Figure 2 and listed in Table S2. Following the Region of Practical Equivalence (to a null effect; ROPE) + 89% High Density Interval (HDI) decision rule, we inferred a practically relevant effect when the entire 89% HDI falls outside of the ROPE^{29,30}. On this basis, we inferred a predictive effect on acceptability judgements for ratings of respect for privacy, trust in the research sponsor, risk of harm, participant benefit from the tracking-data analytics, and data sensitivity. The belief that the research respected people's privacy had the biggest predictive effect on acceptability judgements, with a 1-unit increase in this rating resulting in a 1.72-factor increase in the odds of judging the project as acceptable. On the other hand, the smallest practically relevant effect was for the sensitivity of the data, with a 1-unit increase in this rating resulting in a 1.29-factor decrease (i.e., a 0.78-factor increase) in the odds of judging the project as acceptable. Finally, the posterior distributions of the random intercept effects are shown in Figure S3.

Predictive Model

We also developed a predictive model to assist decision-makers to estimate the social licence of future projects. We trained 3 models on a training dataset: a logistic regression, a mixed effects logistic regression with random intercepts for scenario and participant, and an ElasticNet logistic regression with regularisation hyperparameters, λ and α , chosen via 10-fold cross validation. The mixed effects logistic regression model had the best prediction accuracy (84.31%) on the test data set when compared to the logistic regression model (83.66%) and the ElasticNet logistic regression model (83.66%). The regularisation hyperparameters of the ElasticNet regression were $\lambda = 0$ and $\alpha = 0.15$.

The preferred model — the mixed effects logistic regression — had a Cohen's Kappa of 0.61, indicating that it had 'good' or 'substantial' classification performance^{31,32}. Table S3 shows the parameter coefficients for this model. Given privacy dimension ratings for a new project, these coefficients can be used to predict the likelihood of future acceptability judgements (via the logistic function). To facilitate the ease of this process, we have developed a simple app

(<https://whitejp.shinyapps.io/lumas-predictive-model/>) in which, after entering ratings on each dimension, a user is given a probability in return. This probability can model the percentage of the community that would accept a project with those ratings.

Demographics

Participants were 314 members of the University of Melbourne community (198 female, 111 male, 5 prefer not to say, $M_{\text{age}} = 25.63$, $SD = 8.14$, range: 17–63 years). All participants gave their informed consent prior to the experiment. Twenty-seven participants failed at least one of three comprehension checks, leaving a final sample of 287 participants (184 female, 98 male, 5 prefer not to say, $M_{\text{age}} = 25.59$, $SD = 8.21$, range: 17–63 years).

We endeavoured to match our sample to the distribution of stakeholder types (e.g. undergraduate, postgraduate, academic employee etc.) of the university. Panel E of Figure 3 shows the proportion of each type juxtaposed with the corresponding population figures taken from the University of Melbourne’s 2019 Annual Report³³. Our sample is representative of the students and staff of the University of Melbourne, but no population data is available for the number of other employees or others who regularly attend the university campus and our sample likely underrepresented these demographics.

Panels A–D of Figure 3 show mean participant acceptance judgements broken down by demographic variables. Omnibus ANOVA showed that mean acceptance did not differ by gender, $F(2, 284) = 0.449$, $p = 0.638$, relationship to University of Melbourne, $F(5, 281) = 0.605$, $p = 0.696$, educational attainment, $F(8, 276) = 0.993$, $p = 0.441$, or age group, $F(4, 276) = 0.377$, $p = 0.825$. Simple OLS regression analysis also showed that mean acceptance did not differ by age when treated as a continuous variable, $t(279) = -0.20$, $p = 0.844$.

Figure 3. Acceptability of tracking-data analytics by demographics. (A-D) Mean participant acceptability proportion broken down by age group (A), gender (B), Educational attainment (C), and relationship to the University of Melbourne (D). Acceptability ratings did not differ by any of these demographic variables. Numbers at the bottom of the bars indicate the sample size in that group. (E) The proportion of participants in our sample (blue) from each 'relationship to UniMelb' category compared to that of the university population (red). Note, no population data was obtained for 'other employee' or 'other' categories.

Discussion

In this study we aimed to explore and understand the social licence, or lack thereof, for the use of Wi-Fi location data in university research and service provision. More specifically, we sought to understand whether, to what extent, and under what circumstances, there is social license for location data collection and use. To answer these questions, we presented participants — members of the University of Melbourne community (students, staff, and others) — with 11 hypothetical scenarios depicting the use of Wi-Fi location data on campus. We asked them to rate these scenarios in relation to 11 privacy dimensions, and finally to indicate whether they believed that the use of data in the scenario was acceptable. We then used participants ratings on these 11 privacy dimensions to predict participant attitudes of acceptability, hoping to understand which dimensions are most predictive of social licence.

Establishing the social licence for tracking-data analytics

Our data generally support the notion that, for the hypothetical projects used in this study, there is wide support for the use of University Wi-Fi location data in University research and services. Indeed, the mean acceptance proportion of the scenarios was 71.5%. and all but one (Project TRIIBE) gained more than 50% acceptance. However, social licence is not conceptualised as merely a majoritarian enterprise but rather as requiring the broad support of the community³⁴. Yet, even incorporating a higher acceptance criterion, our data is promising: four of the scenarios (Work Records, Memory for Where, Serving you Better, and Project Fluloc) exceeded 80% acceptability. Of course, exactly where the acceptability criterion should be set by decision-makers as the minimum to establish social licence is likely to depend on contextual factors, and is beyond the scope of this research.

Another consideration relevant to establishing social licence is not just the degree of acceptance of a project, but also how this acceptance is distributed; that is, support for a project must be manifest across the various constituent groups of a community³⁵. Here, our results are promising: acceptability judgements did not differ as a function of gender, age, or educational attainment, suggesting that the

acceptance of tracking-data analytics is not just concentrated to a few groups. Most relevantly, there were also no differences in acceptance judgements between staff (both academic and non-academic) and students (both under- and post-graduate). Given the different interests and incentives between these groups, it was perhaps surprising that acceptance ratings did not differ³⁴.

Factors predicting social licence

Our results also give insight into the factors which are most predictive of social licence. Here, we find evidence that the most predictive factors in determining the social licence for tracking-data analytics on the university of Melbourne campus is the perception that the research team respects individual privacy, the trust in the research team, the degree to which people personally benefit from the project, the sensitivity of the data being collected and used, and the risk of harm inherent in the project.

Surprisingly, however, the perception of the public benefit of a project did not show strong evidence of increasing the likelihood of project acceptability, nor did the perception of private or commercial benefit; only a personal benefit did. Thus, clearly identifiable and more imminent benefits that flow directly to those whose data are being collected and used, are more likely to increase social licence than more diffuse, amorphous public benefits.

Our findings also suggest limited predictive ability of a one-time opt-in/opt-out distinction on acceptability. Indeed, we found that perceptions of the initial difficulty of declining to have one's data collected and used in a project was less strongly predictive of acceptance than perceptions of how much ongoing control over their data users had (e.g., control over how and when one's data was collected, and personal ability to view and delete their data). This may have implications for privacy law which, in Australia and often elsewhere, considers consent as a requirement, not ongoing control of data³⁶.

Finally, the strong effect of trust in increasing the likelihood of acceptance is in line with previous work which suggested that trust was the primary factor underlying social licence for a proposed coal seam gas mine³⁷. Similarly, the strong effect for 'respect for privacy' shows how acceptance of

privacy-encroaching technologies relates to peoples' perceptions of how such technologies affect their privacy. As such, our findings are broadly in line with the notion that people undertake a privacy calculus in which they weigh the benefits of a technology with the negatives and risks of their privacy being compromised³⁸.

Estimating the social licence of future projects

We further provide a simple approach to estimate the social licence of future projects that may be of use to university ethics boards or decision makers. We have built a forward-looking predictive regression model which takes ratings of a university project that involves location data collection and analytics on 11 dimensions and predicts what proportion of the university community, given those ratings, will consider the project acceptable. Decision makers could use this to estimate the social licence for their proposed projects. To best do so, decision makers could get a small sample of independent ratings for their project on the 11 dimensions, take the mean rating for each dimension, and input these into the model to obtain an estimate of the proportion of community members who would likely view the scenario as acceptable, given the scenario ratings. To facilitate this, we have created an online app (<https://whitejp.shinyapps.io/lumas-predictive-model/>). This ability to prospectively estimate social licence will allow decision-makers to either drop projects with little prospect of community support, or to make changes to project details (that are reflected by altered independent ratings on the 11 dimensions) to increase community acceptability.

Limitations

We should be careful to extend these findings too far beyond the university domain. In particular, we should be careful to generalise to significantly different contexts such as government surveillance for which there are specific considerations and a large literature^{39–42}. Future work should consider the social licence for tracking-data use and collection in a wider context and sample^{43,44}. Crucially, social licence

requires openness and transparency to inspire trust and confidence in uses of data. The authors' note with emphasis that social licence is highly context dependent, and hope that the innovative methodological process described in this paper can be used to help uncover trustworthy uses of data in a given context, as part of an open dialogue with those who provide the data in the first instance. While the methodology offers a process for predicting acceptable uses, it is not a panacea but an additional tool in the suite of governance mechanisms for trustworthy data use.

Conclusion

These findings show that a large majority of the University of Melbourne community find the hypothetical scenarios presented to them acceptable. Further, our research suggests that trust of the research sponsor, the belief that they respect people's privacy, the benefit to participants of the research or service, and the sensitivity of the data collected, and the risk of harm imposed by the research, are all important factors which help determine the social licence of tracking-data analytics. Researchers, university management, and those collecting location and other sensitive data, could use these results to cater their data collection and analytics methodology to community commands and expectations. Indeed, doing so will generally increase the efficacy of the data collection and avoid pushback, protest and negative publicity⁴⁵ that may arise from inadvertently stepping out of their social licence.

Considerations of the social licence of tracking-data analytics are only likely to grow in coming years as tracking-data collection and analysis methodologies become easier and more pervasive, and as a result of the widespread uptake of privacy-encroaching tracking technologies by governments around the world in response to the COVID-19 pandemic^{43,44,46}.

Methods

Stimuli and Apparatus

Scenarios

Stimuli were 11 hypothetical scenarios, each of which described a project involving the use of Wi-Fi location data on the University of Melbourne campus. All 11 scenarios are reproduced in full in the supplementary methods and materials, but a summary of each is shown in Table 1.

Privacy Dimensions

Participants rated these scenarios in relation to 11 privacy dimensions on a 0–5 Likert scale. Table 2 is a list of these dimensions, the question posed to participants in relation to each dimension, and the labels used for its Likert scale. Only the most extreme points of the Likert scale were defined, and a slider bar was used between these points.

These 11 privacy dimensions were developed from an extensive literature review and a workshop event in which University of Melbourne Stakeholders including students, academics (from Law, Engineering, Computer Science and Psychology) and professional staff from University Services ‘brainstormed’ the relevant privacy and acceptability dimensions that may affect social licence. The literature review considered research that examined the dimensions underlying ethical tracking-data collection and use from both a normative^{20,47,48} and descriptive/empirical perspective, both qualitative²¹ and quantitative^{23–25}. The final 11 dimensions were drawn qualitatively from an analysis of these sources. For further details of this process, please see the supplementary methods and table S4.

Apparatus

The above stimuli were presented to participants on their own electronic devices through their web-browser, via a survey scripted through Qualtrics.

Procedure

Participants were instructed that they were going to be shown 3 scenarios that they should read carefully. These 3 scenarios were randomly drawn from the list of 11 scenarios and shown to them

sequentially. For each scenario, participants were given an attention check question which asked, “What was the previous scenario about?”. There were 4 randomly ordered response options to this question: the correct answer for the scenario they had just read, and 3 decoy answers drawn randomly from the correct answers for the other scenarios. Participants that failed at least one of these attention check questions were excluded from analysis.

Participants were then asked to rate each scenario on a 0–5 Likert scale in relation to the 11 privacy dimensions. Participants rated each of their 3 randomly drawn scenarios contemporaneously on each dimension to allow for comparative scaling. While doing so, participants were provided with the scenario text below for them to refer to if necessary. The dimensions were presented to participants in the top–bottom order indicated in Table 2. After rating each scenario on each dimension, participants were asked ‘whether the proposed use of university data in each scenario was acceptable’ and gave a binary yes/no response. Finally, participants were asked some demographic questions: their age, gender, educational attainment, and their relationship to the University of Melbourne.

Statistical Analysis

Descriptive Model

Bayesian generalised linear mixed modeling (GLMM) was used to predict participant’s acceptability judgements as an additive function of their privacy dimension judgements. Random intercept effects were included in the model to account for the dependency of the data introduced by different participants rating different scenarios. Thus, all random effects were blocked by participant and scenario. These random effects can be thought of as modelling the acceptability that is inherent in the participant or scenario that is not captured in the model’s fixed parameters (the privacy dimension ratings and interactions therebetween). The privacy dimension Likert ratings were treated as numeric data for the purposes of modeling. The best-fitting model was also estimated with monotonic effects that preserve the ordinal nature of the Likert ratings⁴⁹. This model performed worse for out-of-sample

predictive accuracy (see supplementary materials), providing support for treating these Likert ratings as numeric in all the analyses reported in this paper.

Posterior distributions of model parameters were estimated using Hamiltonian Markov Chain Monte Carlo No-U-turn Sampling implemented in the R package *brms*⁵⁰, a high level interface to Stan⁵¹. Four chains with 2000 iterations (including 1000 ‘burn-ins’) were used. Uninformative priors were used for the intercept and random effect standard deviation parameters; both were Cauchy distributed with a location parameter of 0 and a scale parameter of 2.5^{52,53}. Weakly informative priors were used for all fixed effect coefficients: a Laplacian (double exponential) distribution with a location parameter of 0 and a scale parameter of 0.2 (1 / range).

We developed two plausible candidate models: one which included one parameter for each privacy dimension, and one which also included some *a priori* interaction parameters between privacy dimensions (see Table S1). Model selection between these models was conducted via Pareto-smoothed importance sampling leave-one-out cross validation using the *loo* package²⁷ in R: the model with the highest expected log predictive density (ELPD) was preferred.

To make inferences about the existence of effects, we used the Region of Practical Equivalence (to a null effect; ROPE) + 89% High Density Interval (HDI) decision rule: infer an effect if the entire 89% HDI falls outside of the ROPE^{29,30}. The region of practical equivalence was deemed to be any effect that causes less than a 5% increase or decrease from the mean acceptability proportion over the entire range of the variable. In this case, the ROPE was thus ± 0.098 .

Predictive Model

Data was randomly split into a training (80%) and testing set (20%) grouped by participant so that no participant’s data was used in both training and testing. 3 models were fit on the training dataset via maximum likelihood estimation and then evaluated on the test dataset, using classification accuracy as the model selection metric. The logistic regression and the mixed effects logistic regression were

408 estimated with *lme4*⁵⁴. ElasticNet logistic regression was conducted using *caret*⁵⁵ and *glmnet*⁵⁶. 5-repeat
409 10-fold cross validation was used to tune regularization hyperparameters, α and λ , via a grid search (all
410 combinations of α and λ for $A = \{0, 0.05, 0.1, \dots 1\}$ and $\Gamma = \{0, 0.05, 0.1, \dots 2\}$), again using
411 classification accuracy as the metric. For prediction in the test dataset, the random intercepts from the
412 mixed effects model were dropped, and only fixed effects were used.

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527

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545 **Table 1. Summary of scenarios presented to participants.**

Scenario Name	Scenario Summary
Work Records	University services develop a web-based platform to enable workers on campus to log their working hours and track their working locations through Wi-Fi data, allowing the University to improve service quality and worker safety. Workers usage of the web-based platform is compulsory.
Memory for Where	Researchers collect participants' location via University Wi-Fi data, and later undertake an experiment in which participants recall where they were at certain times. This research seeks to understand people's memory for location and determine what factors influence the errors they make. Participants must opt-in to the study and are paid \$50 for their data and \$15 for completing the memory experiment.
Serving you Better	The University uses Wi-Fi location data and analysis techniques to monitor the use of university food outlets and common areas to better understand the factors that drive the use of these facilities, and how to provide students with a better university experience. No analysis of individual patterns will be undertaken, only aggregated statistical trends. Students can opt-out of the project if they wish.
Safe Campus	Academic researchers collaborate with a start-up firm to use university Wi-Fi data to develop a smartphone app that allows people to be matched with 'walking buddies' to keep them safe at night on campus.
Student Wellbeing Project	The University uses student data, including their W-Fi location data, in a learning analytics system to help improve mental health and identify at-risk students. Students must opt in to participate, and are paid \$20 for doing so.
Project Move	The University collaborates with Yarra Trams to use university Wi-Fi location and timetable data to improve public transport availability and provide information about likely wait-times and occupancy.
Project TRIIBE	University campus shopping and food retailers, collaborating with researchers, use location and internet history data to develop methods to capture and analyse indoor shopping behaviour across shoppers' physical, online, and social environments, to improve customer experience. Participants are paid \$100 for their data and must opt in to participate.
Project QueueSense	Researchers collect Wi-Fi location data at select locations on campus (such as café outlets) to develop algorithms to reduce queueing times at these locations. Coffee will be discounted during the 1-month period of data collection
Project Fluloc	University researchers collect data of social interactions based on indoor Wi-Fi tracking and online health questionnaire data, to assess the role of professional and educational environments in the spread of influenza.
Project Precinct Change Management	University researchers, collaborating with University Services and the Facilities Management Metro, develop algorithms and computational methods to understand the impact of construction disturbances on campus operations and develop methods for improved space use.
Impact of Attendance on Academic Performance	Researchers use Wi-Fi location data to track a cohort of students for one semester to understand how university attendance and presence affects academic and other outcomes.

547 **Table 2. Summary of privacy dimensions on which each scenario was rated.**

Dimension	Question	Likert response
Decline Difficulty	How easy is it for people to decline participation in the proposed research?	0 = 'Extremely easy' 5 = 'Extremely difficult'
Private Benefit	How much would private entities benefit from the proposed research?	0 = 'Not at all' 5 = 'Extremely'
Participant Benefit	How much would participants (i.e., the people whose data is being collected) benefit from the proposed research?	0 = 'Not at all' 5 = 'Extremely'
Public Benefit	How much would the public benefit from the proposed research?	0 = 'Not at all' 5 = 'Extremely'
Disproportionality	To what extent are the researchers only collecting the data necessary to achieve the purposes of the proposed research?	0 = 'Researchers collecting only necessary data' 5 = 'Researchers collecting vast amounts of unnecessary data'
Sensitivity	How sensitive is the data to be collected by the proposed research?	0 = 'Not at all sensitive' 5 = 'Very sensitive'
Risk of Harm	How serious is the risk of harm that could arise from the proposed research?	0 = 'Extremely low risk of harm' 5 = 'Extremely high risk of harm'
Trust	How much do you trust the sponsor of the proposed research?	0 = 'Not at all' 5 = 'Extremely'
Data Security	How secure is the data that would be collected from the proposed research?	0 = 'Not at all secure' 5 = 'Extremely secure'
Ongoing Control	To what extent do participants have ongoing control of their data? This includes controlling how and when data is collected, and having access to view and delete data after it is collected.	0 = 'No control at all' 5 = 'Complete Control'
Respect for Privacy	To what extent do you believe the proposed research respects participants' privacy?	0 = 'Not at all' 5 = 'Extremely'

548

Supplementary Materials

Materials and Methods

Scenarios

Below we reproduce the final scenarios in full as presented to participants.

Project Title: **Work Records**

Workers from overseas in temporary contracts often face dangerous employment conditions in which they are often underpaid or even harassed when working night shifts in deserted buildings. In this project, researchers will develop a web-based platform that enables foreign temporary workers on campus to log their working hours and track their working locations, and allows University Services to access this data to improve service quality and worker safety. Researchers will be allowed to access the data for advanced data analytics, optimization of tours, and prediction of work behaviour. The research results will be published in scientific journals and conferences, with a focus on the algorithms developed and the experimental validation of them. All published data and diagrams will be aggregate results. The original data will be stored in a secured database for five years and then destroyed, as per university data retention policy. The novel methods developed can then be deployed in facility management services in the future.

Project Title: **Memory for Where**

Project Innocence estimates that between two and five percent of people in prison have been wrongfully convicted. Juries will often attribute the provision of a false alibi to guilt; however, it is not uncommon for people to misremember where they were. In this study, researchers will investigate people's ability to recall where they were at a given time to determine what factors influence the errors they make. The ultimate objective is to provide the legal system with a better understanding of when a faulty alibi is likely to occur and to prevent false convictions. Researchers will collect location data via Wi-Fi

connections when participants log onto a university router. Subsequently, participants will also be asked a series of questions about where they were at certain times. Only results aggregated over many people will be released. These will appear in academic papers. All participant data will be stored in a secured server hosted by the University of Melbourne. All transmission of information across networks will occur in encrypted form. Participants will have the capacity to delete their data. Funds for the project come from the Australian Research Council Discovery Program DP312859467. Participants must opt in and will be paid \$50 for their data and \$15 for completing the memory experiment.

Project Title: **Serving You Better**

As part of its redevelopment of the campus, the University would like to introduce monitoring of the use of food outlets and common areas in order to understand better the factors that drive use of these facilities and how we can provide students with a better experience. A combination of technologies will be used, including thermal imaging in indoor areas to detect the presence of people and collection of data from Wi-Fi access points showing the number of devices connected and the duration of stay in an area. The data from the Wi-Fi access points will have login and device IDs removed and replaced with randomly generated IDs. This data will be analysed for statistical purposes only. No analysis of individual behaviour patterns will be undertaken. The data will be securely housed on AWS servers and analysed by University staff in conjunction with other data, such as weather and timetable data. The results will be used to inform University campus strategy, for example by identifying factors that influence the use of indoor and outdoor spaces in order to better meet future demand. The data will be made available to researchers on a case-by-case basis following ethics clearance from the University. Aggregate (i.e., not individual) data showing trends will be published as open data for reuse by the broader community. People who do not wish for their data to be stored can email the researchers for it to be deleted.

Project Title: **Safe Campus**

In the era of #metoo, there is growing awareness that the campus is not necessarily a safe environment after dark. Academic researchers will engage with a start-up firm to develop a walking companion by night app. The project will be funded by the Australian Research Council through their Linkage Program. Registered users of this app will consent to be tracked continuously and to receive messages in set time windows about possible companions nearby for a real-time matching process. They also accept that their identity and location will be revealed to a matching companion, similar to a taxi service. Twelve hours after a matched walk, the record of the identities will be deleted. The tracking data, however, will further be used for data analytics on pedestrian footfall on campus in order to make travel recommendations. The academics plan to publish their data analytics solutions and the start-up will offer an innovative service to people staying on campus.

Project Title: **Student Well-Being Project**

Universities are facing rising mental health problems amongst students, raising questions about whether universities are providing enough support for student emotional and mental health. As a result, the University of Melbourne is investing in a learning analytics system that will pull together different kinds of data to identify at-risk students. The system combines individual level data, such as attendance and assessment data, with aggregated (i.e., not individual) data such as location data via Wi-Fi connections when people log onto a university router. The system will generate ‘flags’ that are associated with events and movements that are potential signs of concern. Multiple flags will trigger an early warning alert and an intervention measure such as a meeting with a student support professional. In the first stage of the project, University of Melbourne researchers will trial and perfect the system ready for roll out next year. Researchers will access participants’ personal data including attendance and assessment results, and track participant location (via their Wi-Fi connections) when they are on campus. No personal information will be released, but researchers will publish the study’s findings, including a prototype

system, in academic papers. All data will be stored in a secured server hosted by the University of Melbourne for 3 years, before being destroyed. Funds for the project come from the University of Melbourne, and participants will be paid \$20 for their participation in their study, for which they must opt in.

Project Title: **Move**

At particular peak times, the tram stops around campus are overcrowded. Researchers suggest improving the situation by short-term predictions of public transport demand from university timetable information, theatre occupancy data collected from the Wi-Fi network, weather data, and machine learning of correlations (patterns) over time. For this purpose, they are requesting access to location data of the population (taken via participants' Wi-Fi connections) on campus over the past year and in real-time. Yarra Trams agrees to sponsor the research project, expecting to adapt their frequencies more flexibly to the actual demand. People, equipped with information about demand and remaining waiting times, might choose alternative transport stops, alternative modes of transport, or just decide to have a coffee first.

Project Title: **Project TRIIBE**

University campus shopping and food retailers currently do not have detailed information about their customers, their shopping patterns and information needs. This puts them at a disadvantage compared to online retailers who have detailed user statistics. Project TRIIBE researches methods to capture and analyse indoor shopping behaviour across shoppers physical, online and social environments, to improve customer experience. The project will collect Wi-Fi connection data and internet access history per visitor. The research team will develop privacy-aware recommendation methods based on aggregate online and physical behaviour. The project will release only a technical description of the machine learning model and a method for how a recommender system implementing this model can be

developed, as well as the estimate of the relative significance of physical, online and social behaviours for recommendations. Only aggregate (i.e., not individual) statistical information will be released in academic papers. Users' data will be stored in an encrypted format, on a secure server and accessible only to the university research team sponsored by ARCLP792534861. Participants will be paid \$100 for their data for a month, and must opt in to participate. Industry partners will use only the developed method to improve their services, with their own data.

Project Title: **Project QueueSense: Measuring Queuing Behaviour**

The need to optimise the workforce and quality of service in retail, airports and front-desk services requires an efficient means to monitor queue length and service times. This project will develop methods to measure queue times based on Wi-Fi signal sensing. A few selected locations (such as café outlets) around the University will be re-configured and equipped with Wi-Fi sensing devices to collect data about customers present on premises, and the length of time spent in queues. The data collection will run over a one-month period. Only information about Wi-Fi equipped devices will be collected. Shoppers will be notified that their dwell time will be monitored while they purchase refreshments on premises through posters placed outside the cafes. Coffee will be discounted during the period of data collection. Only aggregate (i.e., not individual) statistical information will be released in academic papers. Users' data will be stored in an encrypted format, on a secure server and accessible only to the university research team sponsored by ARCLP849537612. The project is conducted with Ethics approval from the University of Melbourne. Industry partners will use only the developed method to improve their services, with their own data.

Project Title: **Project Fluloc: Understanding the Spread of Influenza**

Epidemiological models of influenza spread have been previously developed to predict seasonal influenza epidemics in entire nations, and more recently, in large cities. It is well documented that co-

674 location at work and at schools contributes to the spread of the flu. This project will collect data of social
675 interactions based on indoor Wi-Fi tracking across campus to assess the role of professional and
676 educational environments in the spread of influenza. The project will collect Wi-Fi connection data per
677 user, complemented with an online health status questionnaire to all users of the university Wi-Fi, during
678 the flu period of 2020. The research team aim to improve epidemiological modeling methods for urban
679 precincts. The project will release, in academic papers, a technical description of the model and
680 aggregate-level (i.e., not individual) statistics about the influenza season in 2020. The model will inform
681 epidemiological management practices across educational and professional environments. Data will be
682 stored in an encrypted format on a secure server accessible only to the university research team. The
683 project is sponsored by the Department of Health and has Ethics approval from the University of
684 Melbourne.

685

686 Project Title: **Project Precinct Change Management**

687 Large university campuses embedded in the urban environment are regularly impacted by large
688 infrastructure works, such as the Metro tunnel. The ability to analyse the population dynamics on
689 campus in a fine-grained manner would allow the university to optimise campus disturbances by
690 reallocating space-use and making time-management and scheduling modifications for university
691 activities. In this project, researchers will collect individual data from Wi-Fi users on campus and
692 aggregate it to explore statistical data analytic methods enabling researchers to quantify the impact and
693 economic cost of construction disturbances on campus operations, and research statistical optimisation
694 methods for improved space use. This is an applied research project supported by the University
695 Services and Facilities Management Unit. Findings of the project will directly inform operations on
696 campus during the Metro tunnel construction and may inform further management guidelines. The
697 research will be conducted with ethics approval from the University of Melbourne. No individual data
698 will be released beyond a highly securitised server at the University of Melbourne. Aggregate data

analytics will be produced in a dashboard environment for University Services and used as illustrations in publications and reports. Only aggregate-level (i.e., not individual) data will be used in publications.

Project Title: **The Impact of Attendance on Academic Performance**

Attendance in lectures is falling. As students juggle competing family and work commitments, the number of students appearing in class can drop 60-70% during the period of a semester. While some lecturers are concerned that the quality of the educational outcomes that universities provide is compromised by this dynamic, others contend that online materials provide a superior student experience, especially in large classes. In this study, researchers will track a random cohort of students for one semester and analyse how much time they are spending on campus and which classes they are attending. Their location data will be cross referenced with their academic results at the end of the semester. In order to minimize the impact of selection effects, researchers will use previous academic performance to account for variation in ability between participants. Students must opt-out if they do not wish their data to be recorded. The results will be used to guide university decision-making about the relative emphasis that should be given to online and offline activities. Only aggregate (i.e., not individual) results will be published.

Developing the Scenarios

12 draft scenarios were developed by the living lab for urban mobility and adaptive space use (LUMAS) team at the University of Melbourne that described different scenarios for research use of Wi-Fi data. These 12 scenarios were early drafts of the final scenarios presented in this paper (and one that was removed due to excessive similarity with another scenario). They were edited for simplicity of reading, length, to remove references to ‘de-identified data’, and to ensure there was sufficient variability in the scenarios among the final dimensions.

Developing the Privacy Dimensions

Participants at the LUMAS workshop were placed into small groups and performed a best-worst ranking of 6 randomly drawn (of the 12) draft scenarios. Afterwards, participants discussed the various dimensions that influenced their acceptability in terms of best to worse scale and a preliminary list of relevant dimensions was made. The 12 draft scenarios were then analysed in terms of these dimensions in small groups. Afterwards, the whole group identified dimensions that they felt were relevant but were not raised by their scenarios, as well as dimensions raised by their scenarios but had not yet been captured, as well as dimensions they felt were missing.

This list of dimensions was then reduced to the final 11 dimensions to make the experiment shorter for participants and thus maximise the quality of collected data. This was done by a qualitative process in which the original dimensions were combined to higher-order or similar categories, removed when not relevant to the scenarios or too difficult to experimentally manipulate in the present experiment. This process was also informed by prior empirical and normative work which considered the dimensions or factors underlying the acceptability of tracking and surveillance^{20,21,23,24,47,48}. Table S4 is a summary of how the 24 workshop dimensions were reduced to the 11 final dimensions.

Results

To assess the reasonableness of our assumption to treat the ordinal Likert data as numeric in our modeling, we compared the best-fitting model presented in the paper (i.e., with no interaction effects) with the same model except treating predictor variables as ordinal, and parameterizing them with monotonic effects⁴⁹. The model using monotonic effects (ELPD = -348.35, *SE* = 18.63) fit worse than the best-fitting model presented in the paper (ELPD = -345.22, *SE* = 17.54). For further details of this analysis, see <https://osf.io/mx948/>.

747 **Supplementary Figures**

748

749 **Figure S1. Participant ratings on privacy dimensions, by dimension.** Participant ratings of each
750 privacy dimension for each scenario, organised by privacy dimension. Letters on boxplots
751 indicate the mean ratings of each privacy dimension for each scenario.

Figure S2. Participant ratings on privacy dimensions, by scenario. Participant ratings of each privacy dimension for each scenario, organised by scenario. Letters on boxplots indicate the mean ratings of each privacy dimension for each scenario.

Figure S3. Random effect posterior distributions. (A) Posterior distributions of scenario random intercepts from the preferred model. Point estimates are posterior modes and intervals are 89% highest density intervals. **(B)** Summary of participant random intercept posterior distributions. Black point estimates are posterior means, red point estimates are posterior modes, and blue intervals are 89% highest density intervals.

763 **Supplementary Tables**764 **Table S1. Interaction effects included in candidate model.**

A Priori Interaction Effects	
Private benefit, Participant benefit, & Public benefit	Private benefit & Participant benefit
Private benefit & Public benefit	Participant benefit & Public benefit
Risk of harm & Decline difficulty	Risk of harm & Ongoing control
Security & Sensitivity	Sensitivity & Ongoing control
Trust & Sensitivity	Trust & Risk of harm
Trust & Security	

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766 **Table S2. Parameter posterior distribution summary statistics for model parameters.**

Parameter	Mode	exp(mode)	89% HDI	% HDI in ROPE	Rhat
Intercept	-1.55	NA	[-2.64, -0.52]	NA	1.00
Decline Difficulty	-0.05	0.95	[-0.17, 0.04]	74.3	1.00
Private Benefit	-0.04	0.96	[-0.17, 0.06]	79.44	1.00
Participant Benefit	0.26	1.29	[0.14, 0.42]	0	1.00
Public Benefit	0.14	1.15	[0.01, 0.29]	26.93	1.00
Disproportionality	-0.09	0.93	[-0.22, 0.04]	56.02	1.00
Sensitivity	-0.24	0.78	[-0.43, -0.10]	0	1.00
Risk of Harm	-0.29	0.75	[-0.45, -0.14]	0	1.00
Trust	0.49	1.63	[0.34, 0.68]	0	1.00
Data Security	0.12	1.13	[-0.01, 0.30]	32.01	1.00
Ongoing Control	0.21	1.23	[0.08, 0.36]	3.54	1.00
Respect for Privacy	0.54	1.72	[0.36, 0.70]	0	1.00
Scenario random intercept <i>SD</i>	0.42	NA	[0.11, 0.78]	NA	1.00
Participant random intercept <i>SD</i>	0.86	NA	[0.40, 1.28]	NA	1.01

Note. ROPE = Region of practical equivalence, HDI = Highest density interval, N = 861.

767

768 **Table S3. Parameter coefficients for predictive model.**

Parameter	Coefficient
Intercept	-1.36
Decline Difficulty	-0.15
Private Benefit	-0.12
Participant Benefit	0.27
Public Benefit	0.11
Disproportionality	-0.06
Sensitivity	-0.32
Risk of Harm	-0.31
Trust	0.55
Data Security	0.32
Ongoing Control	0.18
Respect for Privacy	0.55

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770 **Table S4. Developing final privacy dimensions from workshop dimensions.**

Dimension from LUMAS workshop	Notes re conversion to final dimensions
Opt-in/opt-out	<i>Retained</i> as ‘Decline difficulty’.
Transparency	<i>Removed</i> because is difficult to rate from scenario descriptions.
Commercial v Non-commercial benefit	
Personal Benefit	
Who Benefits? How Much?	<i>Combined</i> in final dimensions as ‘Participant Benefit’, ‘Private Benefit’, and ‘Public Benefit’.
Public Benefit v Private Benefit	
Benefit Sharing	
Training and Capacity Building	
Proportionality	<i>Combined</i> in final dimensions as ‘Disproportionality’.
Scope of Data	
Risk of Harm	<i>Retained</i> .
Sensitivity	<i>Retained</i> .
Bona fide	
Track record	<i>Combined</i> in final dimensions as ‘Trust’.
Conflict of interest	
Evaluation and monitoring	
Equality	<i>Removed</i> because is difficult to determine empirically and is hard to define clearly in survey.
Security	<i>Retained</i> in final dimensions as ‘Data Security’.
Use/Reuse/Retention	
Ongoing Subject control	<i>Retained</i> .
Where/What results released	<i>Removed</i> as no variability among scenarios. In each, only aggregate information was to be released, and this is generally the case for university research.
Licensing	<i>Removed</i> because not used in scenarios, and unlikely to be understood by the general population.
Data Linkage	<i>Subsumed</i> under ‘Risk of Harm’ dimension.
	‘Respect for Privacy’ dimension added after literature review.

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