Centre for Economic Performance

Discussion Paper

ISSN 2042-2695

No. 1932
Revised June 2024
(Replaced July 2023 version)

Back to Edgeworth? Estimating the value of time using hedonic experiences

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Abstract
Following early economist Francis Y. Edgeworth's proposal to measure people's hedonic experiences as they go about their daily lives, we use a smartphone app that over seven years randomly asked a panel of 30, 928 UK residents (N = 2, 234, 753) about their momentary happiness and activities to estimate the value of time (VOT), a key input into cost-benefit analyses. Exploiting the randomised timing of surveys for identification, we arrive at a VOT of £−12 (\$ − 15) per hour of commuting and £−24 (\$ − 31) per hour of waiting during commuting (e.g. due to congestion). A person who is stuck in traffic for one hour, therefore, would need to be compensated £24 (\$31) to achieve the same level of happiness as a person who is not. Our unique data, which reflect the richness of people's lives, also allow us to estimate the VOT for 41 other daily activities. We are the first to value time, or indeed anything else, using hedonic experiences in real-time, which has the potential to value other intangibles too.

Key words: value of time, time use, monetary valuation, cost-benefit analysis, happiness
JEL Classification: R4; D61; I31

This paper was produced as part of the Centre's Community Wellbeing Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We are grateful to Richard Layard for his comments and suggestions throughout this project, to Iven Stead and colleagues at the UK Department for Transport (DfT) as well as to Harman Sagger and colleagues at the UK Department for Culture, Media and Sport (DCMS) for their advice. We thank Andrew Clark, David Frayman, Paul Frijters, Carol Graham, Daniel Hamermesh, David Johnston, John Nellthorp, Ekaterina Oparina, Andrew Oswald, Raúl Sanchis, Anna Schulze Tilling, Almudena Sevilla, and Ashley Whillans for their comments, as well as participants at the 2024 Annual Conference of the Royal Economic Society, 2023 Annual Conference of the American Economic Association, 2022 Annual Conference of the European Economic Association, LSE Wellbeing Seminar, LSE Behavioural Science Research Seminar, Oxford University's Wellbeing Research Centre Seminar, CEP Annual Conference, Oxford University's Wellbeing and Policy Conference, and Monash University's Workshop on the Economics of Health and Wellbeing. Nils Mallock and Pengyu (Leo) Li provided excellent research assistance. We are indebted to all Mappiness Study participants. The study was funded by the Economic and Social Research Council (ESRC: PTA-031-2006-00280). The research reported in this paper is not the result of a for-pay consultancy. The authors do not have any financial interest in the topic of this paper. There are no known conflicts of interest.
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Published by
Centre for Economic Performance
London School of Economics and Political Science
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1 Introduction

How people spend their time determines how happy they are on a moment-to-moment basis (Kahneman et al., 2004; White and Dolan, 2009; Bryson and MacKerron, 2017) and also how satisfied they are with their lives (Smeets et al., 2019; Sharif et al., 2021). Some argue that time is the ultimate scarce resource. Following this line of argument, the term *time poverty* has gained traction (Giurge et al., 2020), with an active research agenda on how to optimally allocate time (Hershfield et al., 2016; Whillans et al., 2016, 2017, 2019; Whillans and West, 2022). Holt and Vinopal (2023) examine inequality in the time cost of waiting, showing that low-income individuals in the US spend at least six hours more per year waiting for services than high-income individuals.[1]

If markets fail to provide the means for people to optimally allocate their time, there is an economic rationale for public policy to intervene. It is estimated that the average road user loses about 115 hours per year to congestion in the UK, and about 100 hours in the US (INRIX, 2019b,a). These figures point towards a huge potential for investments into congestion-reducing infrastructure. But how shall economists value time and potential time savings, key inputs into cost-benefit analyses?

In this paper, we propose a new method to value time. We use a smartphone app that randomly surveyed individuals longitudinally about their momentary happiness and activities as they went about their daily lives. We apply our method to value time during 42 daily activities (including commuting, working, providing care or help for adults, and many more). Beyond average values, we look at heterogeneous values by gender, income, time of day, and day of week. Our estimates are based on a unique panel of 30,928 UK residents over seven years ($N = 2,234,753$).

Time use and its value lie at the heart of economics.[2] There exists an established literature that attempts to put a price tag on time, dating back to seminal work by Becker (1965). Here, market goods and time are inputs into household production and a time budget is split between labour and leisure so that leisure time – as a broad category – is valued at the wage rate (its opportunity cost). Other studies have extended this work, for example Johnson (1966), Oort (1969), and Evans (1972), who develop the idea that working hours themselves cause disutility,

[1] For an account of how people in the US and elsewhere spend their time, see Hamermesh (2019).

[2] A recent proposal by Krueger et al. (2009) is *National Time Accounting*. The idea is to use data on the hedonic experiences (or happiness) of individuals during various uses of their time to measure societal welfare.

so that leisure time is valued at *more* than the wage rate; DeSerpa (1971), who introduces constraints in time allocation; Pollack and Wachter (1975), who introduce joint household production; or Cauley (1987), who identifies cases where the value of leisure time deviates from the wage rate (e.g. people not working at market wages).

Most empirical studies estimating the *value of time (VOT)* look at reductions in travel or waiting time during commuting (for example, McFadden (1974) looks at urban transport, De Vany (1974) at air travel).[3] These studies can be categorised into two streams.

The first relies on *stated preferences* and includes discrete choice experiments or contingent valuation studies, which directly ask people how much they would be willing to pay for, for example, a hypothetical reduction in travel time due to a new road (Calfee and Winston, 1998). The second relies on *revealed preferences* and consists of: observational studies, such as observing road choices with different travel times and tolls (Lam and Small, 2001; Small et al., 2005; Fezzi et al., 2014; Buchholz et al., 2020); quasi-experiments, such as exploiting exogenous variation in gas prices across areas and recording the willingness to queue longer for a lower price (Deacon and Sonstelie, 1985; Wolff, 2014); or field experiments, such as experimentally manipulating bundles of waiting times and prices offered to users of ride-sharing apps (Goldszmidt et al., 2020).[4]

Overcoming issues such as hypotheticality, studies relying on revealed preferences are often considered the gold standard to value intangibles, including time. These studies generally rely on the assumption that people act rationally and with perfect foresight. While this assumption has desirable analytical properties, it also has three problems.

First, research has shown that the framing of options influences choices, e.g. whether options are presented as a gain or a loss, like "time saved" or "time lost" (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; Kahneman and Tversky, 1984). Likewise, cognitive biases in intertemporal choice (e.g. present bias) are likely to also bias how individuals value time itself (Thaler, 1981; Loewenstein and Prelec, 1992; Laibson, 1997). Second, there is a large body of evidence on prediction errors in economics (Loewenstein et al., 2003; Loewenstein and Adler, 2005) and psychology (Wilson and Gilbert, 2003), showing that individuals make systematic errors when predicting the welfare consequences of particular choices and

[3]A smaller set of studies look at reductions in treatment or waiting time during medical care (cf. Cauley, 1987; Borisova and Goodman, 2002), others at consumer behaviour (e.g. search time for products) (cf. Crafton, 1979).

[4]See Appendix Table A9 for a review of the literature, including estimates by method.

events (cf. Odermatt and Stutzer, 2019). Third, and most important, what constitutes a particular time use is subjective, and the context in which an activity is experienced is key. For example, time spent commuting with a loved one may be experienced differently than time spent commuting alone, or may not be perceived as commuting at all (Kim and Zauberman, 2013; Xu et al., 2020).[5]

We thus propose a new method to value time: *experiential valuation* based on experience sampling. It does not rely on how options are presented to individuals, nor does it require them to predict the welfare consequences of different options. Instead, it looks at their hedonic experiences once they have made their choices.[6] Most importantly, it allows individuals to judge for themselves what constitutes a particular use of their time and how they feel about it.

The idea behind experience sampling (a term coined by psychologists) can in fact be traced back as far as early economist Francis Y. Edgeworth (1845–1926). Edgeworth argued that new technical developments would eventually make it possible to develop a *hedonimeter*, which would allow economists to directly measure utility on a physiological basis. An early behavioural economist, he envisioned the hedonimeter as a "psychophysical machine, continually registering the height of pleasure experienced by an individual, exactly according to the verdict of consciousness, or rather diverging therefrom according to a law of errors" (Edgeworth, 1881, p. 101).

Our method builds on Edgeworth's hedonimeter, with three differences: while Edgeworth's vision was to directly measure utility, we do not require our measure of hedonic experiences – whether an individual feels happy – to be equal to utility. For our purpose, it is sufficient that individuals care about their experiences. Indeed, there is now evidence from choice experiments and vignette studies suggesting that individuals care a great deal about how happy they are, in general and on a moment-to-moment basis (Benjamin et al., 2012; Adler et al., 2017, 2022), and that this predicts their behaviour in a wide range of domains (De Neve and Oswald, 2012; Oswald et al., 2015; Liberini et al., 2017; Ward, 2020; Kaiser and Oswald,

[5] Georges-Knot et al. (2024), exploiting quasi-random variation in the number and timing of paid vacation days in France, show that the self-employed are more likely to take a day off when they can spend that day with their spouse, revealing a higher value of leisure time when spent together. Similarly, Randriamaro and Cook (2022), in a lab experiment eliciting monetary compensations for waiting 30 minutes in an empty room, show that compensations vary substantially depending on whether participants have access to a radio or smartphone.

[6] Our argument mirrors that by Kahneman et al. (1997), who make the distinction between *decision utility* (as measured by both stated and revealed preferences) and *experienced utility* (which we measure here).

2022).[7] The other two differences are practical: we collect data using self-reports, in discrete time. Our method differs from the day-reconstruction method by Kahneman et al. (2004) and conventional time use surveys in that it collects data on hedonic experiences in the moment, rather than asking about them retrospectively using diaries.

Our *hedonimeter* is a smartphone app that asked a panel of $30,928$ UK residents during the years 2010 to 2016 ($N = 2,234,753$) at random moments *(i)* how happy they felt in that particular moment, *(ii)* where they were, *(iii)* whom they were with, and *(vi)* what they had just been doing. In addition, their location was recorded using GPS. We use these panel data to estimate the VOT for 42 daily activities. We provide average and heterogeneous values by gender, income, time of day, and day of week.

Our method has three steps: exploiting the randomised timing of surveys for identification, we first estimate the effect of each activity on respondents' happiness. We then calculate the marginal rate of substitution between each activity and income to obtain the income equivalent of each activity, standardising the duration to one hour. Finally, we obtain the VOT for each activity by subtracting from the income equivalent of that activity the time use-weighted average income equivalent of all the other activities (as counterfactual). Hence, the VOT for each activity is the monetary value of spending one hour in that activity as opposed to doing something else. Our models look at within-individual variation, controlling for other activities respondents may be simultaneously engaged in (multi-tasking), where they currently are, whom they are with, meteorological conditions, and region and time fixed effects. Our results are robust to excluding any of these controls.

We arrive at a VOT of £-11 (\$ $-$ 15) per hour of commuting and £-24 (\$ $-$ 31) per hour of waiting during commuting (e.g. due to congestion).[8] The negative sign suggests that there is an opportunity cost to spending time in these activities and that individuals would be better off doing something else. In particular, a person who is stuck in traffic for one hour would need to be compensated £24 (\$31) to achieve the same level of happiness as a person who is not. This suggests a high social value of investments into congestion-reducing infrastructure. Our VOT of £-12 (\$ $-$ 15) per hour of commuting, in absolute terms, is

[7] Edgeworth himself suggested 'happiness' as the quantity measured by his hedonimeter, being fully aware of its imperfections. Like many early economists, he was pragmatic, arguing that the "greater uncertainty of hedonimetry [...] may be compensated by the greater number of measurements, a wider average; just as, according to the theory of probabilities, greater accuracy may be attained by more numerous observations with a less perfect instrument" (Edgeworth, 1881, p. 102).

[8] All \$ figures are converted from £ using an exchange rate of £1 = \$1.27, current on January 31, 2024.

similar to Goldszmidt et al. (2020), who in field experiments manipulate bundles of waiting times and prices offered to users of the Lyft ride-sharing app, estimating a VOT of \$19 in the US in 2020. This suggests that hedonic experiences yield similar (though not identical) results as observed behaviour, in line with recent evidence by Kaiser and Oswald (2022). Our estimate is also similar to values currently used by UK Government.[9] We find that spending one hour to provide care or help for adults is worth £−18 (\$ − 23), and one hour being sick in bed as much as £−65 (\$ − 82). In contrast, spending one hour doing sports or exercise is worth £17 (\$21), one hour at a theatre, dance, or concert 16 (\$20), and one hour in an exhibition, museum, or library £11 (\$14). Our VOT of £−12 (\$ − 15) per hour of working, in absolute terms, is 75% of the UK median hourly wage in 2023, which is £16 (\$20) (ONS, 2023).

We contribute to the literature that estimates the VOT, which has previously relied exclusively on stated or revealed preferences (Deacon and Sonstelie, 1985; Calfee and Winston, 1998; Lam and Small, 2001; Small et al., 2005; Fezzi et al., 2014; Wolff, 2014; Buchholz et al., 2020; Goldszmidt et al., 2020). Our paper adds a new method. It also allows us to go beyond existing studies that typically have a narrow focus on commuting, or studies that look at broad categories such as "labour" or "leisure". In fact, our unique data, which reflect the richness of people's lives, allow us to estimate the VOT for 42 daily activities. Our sample is also much broader, covering a wider range of individuals than studies relying on smaller-scale experiments or specific groups such as ride-share users. As we will see, it scores well in terms of external validity when comparing it with the UK general population. Our paper also contributes to the literature, mostly in public and environmental economics, that uses hedonic pricing or accounts of life satisfaction for non-market valuation (van Praag and Baarsma, 2005; Luechinger, 2009; Luechinger and Raschky, 2009; Maddison and Rehdanz, 2011; Levinson, 2012; Krekel and Zerrahn, 2017; von Möllendorff and Welsch, 2017; Dolan et al., 2019, 2021; Krekel et al., 2021; Goebel et al., 2022). We show that hedonic experiences in real-time can be used as an alternative (or complement), specifically for non-market goods and services for which no complementary markets exist or which are too granular to be captured by life satisfaction, such as infrequent time spent in various activities. Our method enables statis-

[9] The UK Department for Transport (DfT) uses a value of time during commuting (when private, which includes all trips to and from work during non-work time) of £13 (\$16), as well as a separate employer's business value of time during commuting (which includes all business trips) of £10 (\$13) for trips by car and £9 (\$11) for trips by rail (DfT, 2022, 2023).

tical agencies to paint a more complete picture of social value in national accounts, better including, for example, household production. It is relatively cheap and easy to implement, allowing for a uniform methodology to calculate the VOT for most activities in people's lives. We are the first to value time (or indeed anything else) using hedonic experiences in real-time, which has the potential to value other intangibles too.

2 Data

We use panel data collected via a smartphone app called *Mappiness*.[10] The app was developed for Apple's iPhone and was distributed via its App Store from 2010 onwards, at no charge.[11] Developed at the London School of Economics, it gained popularity in the UK thanks to widespread media coverage.[12] As a result, a broader range of individuals selected into using the app compared to other, typically much smaller experience-sampling studies (mostly in psychology). The app was described to users as a "research project" that "maps happiness across space in the UK", offering users "interesting information about their own happiness [...]", including "when, where and with whom they are happiest". They could use the app for as long as they wished. Appendix Figures A1 to A4 show screenshots of the app.

Overall, our sample includes $30,928$ unique respondents and a total of $2,234,753$ responses, covering the entire UK (England, Wales, Scotland, and Northern Ireland) over the course of seven years, from 2010 to 2016.[13] The median days of participation are 52, with a mean of 143 and a standard deviation of 467. The median number of responses is 161, with a mean of 72 and a standard deviation of 162. The bottom quartile includes less than 70 responses, the top quartile more than 428.

2.1 Intake Survey

After downloading the app, participants (who had to be aged 18+) were first presented with information about the study, which covered anonymity as well as secure data transfer and storage, and gave their consent to take part. They were then given an intake survey within

[10] http://www.mappiness.org.uk

[11] The app was downloadable from August 6, 2010, until February 4, 2017.

[12] For example, the app was highlighted in the *Featured* section of the App Store for two weeks after its launch. It also featured on television (BBC and CNN), radio, and in the mainstream press, and was shared widely on social media, including Facebook and Twitter.

[13] The app also collected data in 2017 and 2018. We exclude these years as they only constitute 0.8% of observations, but including them makes no difference to our results. We restrict our sample to UK residents, who are the majority, though the app could be downloaded worldwide.

the app, which asked about individual characteristics (age, gender, marital status, health, employment status, and overall life satisfaction) and household characteristics (household income and number of adults and children in the household). This survey was completed only once, prior to and on a different occasion than any collection of data on momentary happiness and activities, so as not to prime respondents. The sign-up process typically took less than five minutes.

Appendix Table A1 shows summary statistics based on the intake survey. On average, respondents are 33 years old (standard deviation of 10), equally likely to be male or female, 80% likely to be in a relationship (though only 32% are married and living with their spouse, 29% including children), and most consider themselves to be in good (32%) or very good health (42%), some even in excellent health (14%). About 80% are employed or self-employed, 12% in full-time education, and 3% unemployed, with a median annual gross household income of £48,000 ($60,960), or £28,000 ($35,560) when equivalised to account for household size and composition. About a quarter of respondents are from London, with the others broadly balanced across the remaining regions of the UK.

2.2 Experience-Sampling Survey

After completing the intake survey, the app started operating: participants were messaged at *random* moments (the default being twice a day between 8am and 10pm) and asked to complete a short experience-sampling survey.[14] Appendix Figure A5 plots the distribution of responses by time of day, showing that the bulk was recorded between 8am and 10pm.

This randomly-recurring survey asked participants about, in the following order to avoid priming: *(i)* how happy they felt in that particular moment; *(ii)* where they currently were (i.e. place and location, single choices which could be exclusively *at home*, *at work*, or *elsewhere* and *indoors*, *outdoors*, or *in a vehicle*); *(iii)* whom they were with (i.e. companionship, a multiple choice which could include *partners*, *children*, *other family members*, *colleagues or classmates*, *friends*, *other people they know*, or *strangers or themselves only*); and *(vi)* what they were currently doing (i.e. 42 daily activities, also multiple-choice to account for multi-

[14]Participants could choose between 1, 2, 3, 4, or 5 messages per day and could specify daily start and end times to the nearest fifteen minutes. Notifications were similar to text messages in terms of sound and vibration.

tasking).[15] The exact timestamp of the response was recorded, and so was the precise location using GPS. When setting up the app, respondents were prompted to complete surveys as soon as possible upon receipt. Each survey typically took no longer than 30 seconds. Completion was incentivised by providing users with frequent, simple, and personalised feedback on their happiness in different contexts.

We restrict our sample to responses initiated within 60 minutes of being messaged and completed within a further five minutes.[16] Appendix Figure A6 plots the cumulative probability of responding by response lag, defined as time elapsed between the random message and response in minutes. As seen, more than 50% of responses occurred within five minutes. The bottom quartile responded within 21 seconds, and the bottom half within three minutes.

Appendix Table A2 shows summary statistics based on our experience-sampling survey. On average, respondents spend large amounts of time on work and related activities: 25% of responses come from *working or studying*, compared to 9% from *commuting or travelling*. An additional 11% come from communicating with others or searching for information, including writing e-mails, text messaging, using social media, or browsing the internet. However, respondents also spend large amounts of time on leisure: 18% of responses come from watching television or movies alone, another 20% from eating or relaxing in one form or another. Note that response shares add up to 1.67, suggesting that respondents are, on average, engaged in 1.67 activities at the same time (i.e. multi-tasking).

Our outcome is feeling *happy*, which is obtained from a slider asking: "Do you feel happy?". Answers range continuously (limited only by the pixel resolution of the device) from zero ("Not at all") to 100 ("Extremely"), the initial position being the midpoint. The median happiness in our estimation sample is 68, with a mean of 66 and a standard deviation of 21). Appendix Figure A7 plots the distribution of our outcome. Our variables of interest are the 42 daily activities for which we estimate the VOT. We use a binary indicator for each activity. For *waiting or queueing*, for example, the indicator is one if a respondent selected "Waiting,

[15]The full list of activities was inspired by both the American Time Use Survey (ATUS) and the UK Time Use Survey (UKTUS), but simpler than either. The order of items was thematically grouped and *not* randomised to make it easier to complete each survey quickly. Regarding place, if respondents were working from home, they were prompted to select *at home*. If they were driving a vehicle, or otherwise unable to answer safely, they were prompted to complete the survey as soon as they safely could.

[16]A cut-off of 60 minutes is chosen so that responses more accurately reflect a probability sample of the moments in a respondent's life. A cut-off of five minutes is chosen so that hedonic experiences remain temporally matched to activities, companionship, and place and location.

queueing" when asked: "Just now, what were you doing?", and zero otherwise.[17]

In Section 5.4, we check our intake and experience-sampling survey for external validity, by comparing our data with the nationally-representative UK Household Longitudinal Study ("Understanding Society") and UK Time Use Survey (UKTUS). As we will see, they score well in terms of external validity.

2.3 Weather Data

We merge our data with administrative data on meteorological conditions from the UK Meteorological Office Integrated Data Archive System (MIDAS) (Met Office, 2006a,b). These include *air temperature* in degrees centigrade, *wind speed* in knots, *precipitation* as a binary indicator for any rain during the hour ending closest to the response time, *cloud cover* and *sunshine* as indicators for any cloud cover and for sunshine (no sun, intermittent sun, and continuous sun), and *daylight* as a binary indicator for daylight. Exploiting the exact geographical coordinates and timestamps of responses, we link each response to the meteorological conditions reported by the nearest weather station at the nearest available date and time.

3 Empirical Strategy

3.1 Estimation

We estimate the VOT for 42 daily activities. Our modelis:

$$\begin{aligned} y_{it} = \alpha + \delta A_{it,k=1} + \beta_1' A_{it,k\neq 1} + \beta_2' P_{it} + \beta_3' L_{it} + \beta_4' C_{it} + \beta_5' M_{it} \\ + r + t_s + t_{hd} + t_{dw} + t_m + t_y + u_i + \epsilon_{it} \end{aligned} \tag{1}$$

where y_{it} is the *happiness* of respondent i at time t; $A_{it,k=1}$ is a dummy that is one if the respondent reports activity $k = 1$ (*waiting or queueing*) when randomly messaged by the app, and zero otherwise; and $A_{it,k\neq 1}$, C_{it}, P_{it}, L_{it}, and M_{it} are time-varying controls.[18] $A_{it,k\neq 1}$ includes dummies for the 41 other daily activities the respondent may be doing at the same

[17]The Online Appendix includes links to the description of the app in Apple's App Store, to the consent form, and to both the intake and experience-sampling surveys.

[18]We cannot control for individual and household characteristics as the intake survey was completed only once, so these characteristics would be collinear with the individual fixed effects. However, we expect any confounding from changes in these characteristics to be minor, as the median days of participation were 37.

time (e.g. a respondent may be *waiting or queueing* whilst *commuting or travelling* or whilst at a *theatre, dance, or concert*, which may result in different hedonic experiences). C_{it} includes dummies for the companionship the respondent may be in (e.g. *colleagues or classmates*), P_{it} for the place (e.g. *at work*), and L_{it} for the location (e.g. *indoors*). Finally, M_{it} includes controls for meteorological conditions. Weather may be a confounder that influences both happiness and the likelihood to engage in certain activities.

We also include fixed effects. In particular, r are region fixed effects at the Middle Layer Super Output Area (MSOA) level that net out systematic differences in time-invariant unobserved heterogeneity in the area where GPS indicates respondents are located when responding. There are $8,925$ such areas in our sample.[19] Moreover, t_s are holiday-season, t_{hd} hour-of-day, t_{dw} day-of-week, t_m month, and t_y year fixed effects that net out differences across time. Finally, u_i are individual fixed effects that net out systematic differences in time-invariant unobserved heterogeneity at the respondent level, e.g. time preferences (cf. Ifcher and Zarghamee, 2011; Lerner et al., 2012; Haushofer and Fehr, 2014) or genetic determinants of happiness (cf. Tellegen et al., 1988; Rietveld et al., 2013; Okbay et al., 2016). Our model is estimated using OLS, with robust standard errors clustered two-way at the region and respondent levels.

We are interested in δ: it is the within-individual change in happiness associated with becoming engaged in activity $A_{it,k=1}$, holding everything else constant. We are also interested in the response share $s_{k=1}$: it is the share of responses reported to be in that activity amongst all responses. For brevity, we re-write Equation 1 as:

$$y_{it} = \alpha + \delta A_{it,k=1} + \beta' X_{it} + r + T + u_i + \epsilon_{it} \tag{2}$$

where X_{it} includes $A_{it,k\neq 1}$, C_{it}, P_{it}, L_{it}, and M_{it}, and T includes t_s, t_{hd}, t_{dw}, t_m, and t_y.

[19] MSOAs capture between $2,000$ and $6,000$ households and have a resident population between $5,000$ and $15,000$ individuals (ONS, 2021).

3.2 Identification

The app has a simple, non-predictable built-in randomisation algorithm.[20] Figure 1 illustrates the algorithm for three experience-sampling surveys per day between 8am and 10pm. The randomised timing of surveys aims to ensure that responses accurately reflect a probability sample of the moments in a respondent's life and, conversely, that respondents do not select into surveys based on their current circumstances.

Our identification exploits the randomised timing of surveys. In particular, when a respondent was messaged is random and hence orthogonal to the start and end time of each activity, allowing us to catch the respondent at the start, end, and any time in-between with equal probability. Moreover, it is orthogonal to the happiness of the respondent. Finally, it is orthogonal to other activities the respondent may be doing at the same time and the current circumstances in which these take place. Some activities and circumstances, however, may be systematically more likely to occur together and, at the same time, may be correlated with happiness, potentially biasing δ and $s_{k=1}$ in Equation 2.[21] We thus routinely condition on time-varying controls and region, time, and individual fixed effects. Our identifying assumption is that selection into activity $A_{it,k=1}$ and its reporting $R(A_{it,k=1}) = s_{k=1}$ (where $R(.)$ is the response function) is quasi-random, conditional on time-varying controls X_{it}, region and time fixed effects r and T, and individual fixed effects u_i.

In Section 5.1, we look at unobservable selection and coefficient stability by selectively excluding other activities, companionship, place and location, and meteorological conditions in X_{it} as well as region and time fixed effects r and T from Equation 2. As we will see, δ remains stable, changing by less than 14%. We also make an additional bounding argument in line with Oster (2019) to elicit the extent of unobservable selection, if present, which shows that unobservables and potential omitted variable bias are of little concern. Note that respondents have the option to select two residual activities if none of the offered fits their current: *something else* and, if they wish to report a customised activity, a free text. A

[20] The algorithm has four steps: first, it allocates three blocks of equal duration between the daily start and end time. Second, it allocates a buffer at the end of each block (of 0.25× the block's duration) to avoid having two consecutive experience-sampling surveys too closely spaced in time. Third, it picks a random moment within each block, avoiding the block's buffer. Finally, it moves each randomly picked moment forward by the same duration, randomly chosen to be between zero and the block's full duration (including buffer), wrapping from the end of the day to its start, to reduce predictability while ensuring a uniform probability sample.

[21] For example, when it comes to activity $k = 1$ (*waiting or queueing*), people who have a chronic illness may be permanently unhappier and, at the same time, may be systematically more likely to be waiting at the doctor's office. Similarly, people may be more likely to be waiting during commuting, which may make them temporarily unhappier.

residual category also exists for location: *elsewhere*. Unobservable activities and locations should be captured by these.

4 Results

Table 1 shows our estimates from Equation 2. We find that activity $k = 1$ (*waiting or queueing*) has a significant, strong negative effect on happiness: it decreases happiness measured on a zero-to-100 scale by 3.6 points.Two percent of responses come from this activity.

Table 1 about here

Looking at the 41 other daily activities, *waiting or queueing* turns out to be the third least enjoyable: only when *sick in bed* (−18.4) or engaged in *care or help for adults* (−3.9) are people less happy. Less than five percent of responses come from these activities. It is followed by *commuting or travelling* (−1.9), *working or studying* (−1.6), and *admin, finances, or organising* (−1.3), which have some of the highest response shares, in particular *working or studying* (25%) and *commuting or travelling* (9%). The most enjoyable activities, on the contrary, are *intimacy* (+12.7), *sports, running, or exercise* (+6.7), and *theatre, dance, or concert* (+6.6). Moderately enjoyable activities include *watching TV or movies* (+2.3, 18%) and *talking, chatting, or socialising* (+4.2, 15%). Activities are generally enjoyed more when outdoors, somewhere other than at home or at work, and in the company of partners or friends.

4.1 Value of Time

We now calculate the VOT for each activity, starting with activity $k = 1$ (*waiting or queueing*), which we denote as $VOT_{k=1}$. It is defined as the monetary value of spending one hour *waiting or queueing* as opposed to the average monetary value of all the other activities, weighted by their relative frequency.[22] By using a weighted average of all the other activities, we assume that observed selection into these other activities constitutes a valid counterfactual, which is a conservative approach.

[22] We standardise the VOT for each activity to one hour for comparability with the literature. When standardising to one hour, we implicitly assume a linear relationship between the hedonic experiences of activities and their durations (or, alternatively, that the hedonic experiences of activities are independent of their durations). Note that, due to random messaging during each episode, our calculated VOT can be interpreted as the average VOT. Under linearity, the average VOT is equal to the marginal VOT.

We find that spending one hour *waiting or queueing* as opposed to doing something else is worth £-13 ($\$-17$), or £$-17$ ($\$-22$) in 2023 prices.[23] The negative sign suggests that there is an opportunity cost to *waiting or queueing* and that respondents would be better off doing something else. In particular, a respondent who is made to wait or queue for one hour would need to be given £17 ($22), on average, to compensate the resulting reduction in happiness.

To obtain $VOT_{k=1}$, we first calculate the marginal rate of substitution $MRS_{k=1}$ between activity $A_{it,k=1}$ and income to arrive at an income equivalent of the activity. Then, we subtract from that income equivalent the average income equivalent of the $k = \{2, 3, 4, ...42\}$ other daily activities, weighted by their response share s_k. We evaluate $MRS_{k=1}$ at the average annual gross household income in the UK in 2016 (the last year during our observation period), scaled to £/hour. Equation 3 shows this calculation:

$$\begin{aligned} VOT_{k=1} &= (MRS_{k=1} - \sum_{k=2}^{42} MRS_k \times s_k) \times Income_{UK} \\ &= (\frac{\frac{\partial y_{it}}{\partial A_{it,k=1}}}{\frac{\partial y_{it}}{\partial Income_i}} - \sum_{k=2}^{42} \frac{\frac{\partial y_{it}}{\partial A_{it,k}}}{\frac{\partial y_{it}}{\partial Income_i}} \times s_k) \times Income_{UK} \end{aligned} \tag{3}$$

where $\partial y/\partial A_{it,k=1}$ is our coefficient for activity $A_{it,k=1}$, i.e. $\delta = -3.6$, obtained from Equation 2; $\partial y/\partial Income_i$ is our coefficient for log annual gross household income, i.e. 0.9, obtained from an auxiliary regression which we discuss in Section 5.2; $\partial y/\partial A_{it,k}$ are our coefficients for the $k = \{2, 3, 4, ...42\}$ other daily activities, likewise obtained from Equation 2; s_k is the response share of each activity, and $Income_{UK}$ is the average annual gross household income in the UK in 2016, which was £19,727 ($25,053) (ONS, 2020), scaled to £/hour.[24] A coefficient for log income of 0.9 and an average income of £19,727 ($25,053) imply that one point of happiness on a zero-to-100 scale for one individual for one hour is worth £2.5 ($3.2).[25]

Table 2 shows the results for the 41 other daily activities, calculated in the same way as in Equation 3.

[23]We adjusted for inflation as follows: VOT 2023 = VOT 2016 × (GDP Deflator 2023 / GDP Deflator 2016) × (GDP Per Capita 2023 / GDP Per Capita 2016)$^{1.3}$. GDP deflator growth comes from the UK's Office for National Statistics (ONS) Series MNF2, real GDP per capita growth from Series IHXW, and 1.3 is the marginal utility of income elasticity (HM Treasury, 2021b).

[24]Note that activities are, at the time of reporting, *duration-less*. This is an advantage: respondents are not required to recall exactly how long they have been engaged in each activity nor how long they will continue to be engaged, which is less susceptible to bias compared to the day-reconstruction method by Kahneman et al. (2004) and conventional time use surveys using diaries. Yet, to calculate $VOT_{k=1}$, we need to lend $\partial y/\partial A_{it,k=1}$ a temporal dimension. We do this by scaling to £/hour.

[25]£$X = ((£19,727/365)/24)/0.9$

Table 2 about here

When it comes to enjoyable activities, we find that spending one hour in *sports, running, exercise* as opposed to doing something else is worth £17 (\$21) in 2023 prices, one hour at a *theatre, dance, concert* £16 (\$20), and one hour in an *exhibition, museum, library* £11 (\$14). On the contrary, spending one hour *working or studying* or *commuting or travelling* is both worth £−12 (\$ − 15), spending one hour to provide *care or help for adults* £−18 (\$ − 23), and one hour *sick in bed* as much as £−65 (\$ − 82). Again, the negative signs suggest that there is an opportunity cost to these activities and that respondents would be better off doing something else. They would need to be compensated by these amounts to achieve the same level of happiness as if they were not engaged in these activities.[26]

4.2 Interactions

Our method is more flexible than previous studies, in that it can be used to calculate the VOT for all possible (combinations of) activities and their contexts, depending on researchers' and policy-makers' interests. To illustrate, we look at the interaction between *waiting or queueing*, i.e. $A_{it,k=1}$, and *commuting or travelling*, i.e. $A_{it,k=2}$, to estimate the VOT for potential time savings from reducing congestion during commuting, which we denote as $VOT_{k=1,2}$. We find that spending one hour in *waiting or queueing* during *commuting or travelling* as opposed to doing something else is worth £−24 (\$ − 31), which is a larger negative effect than either activity on its own ("superadditivity").[27] In other words, there is an opportunity cost *premium* to waiting during commuting (e.g. due to congestion).

To obtain $VOT_{k=1,2}$, we first re-estimate Equation 2 including an interaction between $A_{it,k=1}$ and $A_{it,k=2}$:

$$y_{it} = \alpha + \delta_1(A_{it,k=1} \times A_{it,k=2}) + \delta_2 A_{it,k=1} + \delta_3 A_{it,k=2} + \beta' X_{it} + r + T + u_i + \epsilon_{it} \tag{4}$$

We then calculate $VOT_{k=1,2}$ in the same way as in Equation 3:

[26] Individuals may form expectations regarding certain activities, and depending on activity, reference-dependent preferences suggest that individuals may then be less positively or negatively affected by that activity (Kőszegi and Rabin, 2006). Unfortunately, our data and method do not allow us to capture expectations. Note that individuals may engage in mitigating behaviours to avoid certain activities, if expected.

[27] Table 2: £−17 (\$ − 22) per hour of waiting, £−12 (\$ − 15) per hour of commuting

$$
\begin{aligned}
VOT_{k=1,2} &= (MRS_{k=1,2} - \sum_{k=3}^{42} MRS_k \times s_k) \times Income_{UK} \\
&= (\frac{\frac{\partial y_{it}}{\partial(A_{it,k=1} \times A_{it,k=2})} + \frac{\partial y_{it}}{\partial A_{it,k=1}} + \frac{\partial y_{it}}{\partial A_{it,k=2}}}{\frac{\partial y_{it}}{\partial Income_i}} - \sum_{k=3}^{42} \frac{\frac{\partial y_{it}}{\partial A_{it,k}}}{\frac{\partial y_{it}}{\partial Income_i}} \times s_k) \times Income_{UK}
\end{aligned} \tag{5}
$$

Table 3 shows the results for the 40 other daily activities, calculated in the same way as in Equation 5.

Table 3 about here

Interestingly, we find that *waiting or queueing* makes *any* of the 40 other daily activities less enjoyable, the exception being *sick in bed*. In particular, waiting during enjoyable activities makes these activities less enjoyable, and waiting during non-enjoyable activities makes these activities even less enjoyable. Accordingly, a respondent who is made to wait or queue for one hour in any of these activities would need to be compensated for the resulting reduction in happiness, for non-enjoyable activities over and beyond the standard rate. From a welfare perspective, there is a rationale for reducing idle time.

4.3 Heterogeneity

Beyond averages, we can also look at heterogeneity by gender; household income (lowest and highest quartile); time of day (morning, afternoon, and evening); and day of week (weekday and weekend); for each activity as well as for interactions. To do so, we run the same regressions as in Equations 2 and 4, and conduct the same calculations as in Equations 3 and 5, using sub-samples split by group. Note that coefficients for activities $A_{it,k}$ and associated response shares s_k are now group-specific. Tables 4a and 4b show our results.

Tables 4a and 4b about here

We find substantial heterogeneity in our VOT estimates, in particular by gender and household income. More specifically, women suffer more than men from *waiting or queueing* in general, and so do low-income compared to high-income households. When *commuting or travelling*, and even more so when subject to congestion or delays (*waiting or queueing* whilst *commuting or travelling*), we find that women and low-income households again suffer (substantially) more. Accordingly, they would need to be compensated relatively more for the resulting reduction in happiness. When it comes to time of day or day of week, there is more disutility from commuting and from congestion or delays on evenings and on weekends.

Apart from these, Tables 4a and 4b show similar heterogeneity for many other activities (e.g. women suffer more from providing care or help for other adults and also enjoy childcare less than men, hence require different compensatory payments). This highlights the importance of using VOT estimates specific to target groups in welfare analyses.

5 Robustness

Our VOT depends on *(i)* our estimate of the effect of being engaged in an activity on happiness when randomly messaged by the app and *(ii)* our estimate of the effect of income on happiness. In what follows, we check the robustness of each. We also look at estimation, by scrutinising our linear models. Finally, we check our intake and experience-sampling survey for external validity.

5.1 Unobservable Selection

We first look at our estimate of the effect of being engaged in an activity on happiness, using activity $k = 1$ (*waiting or queueing*) as an example. In particular, we test the stability of δ in Equation 2 by first estimating a parsimonious model that includes only individual fixed effects and then successively including more controls, to elicit the extent of unobservable selection.

Appendix Table A3 shows our results. Column 1 includes only individual fixed effects, whereas Column 2 adds region and time fixed effects r and T and Column 3 time-varying controls X_{it}, including other daily activities the respondent may be doing at the same time $A_{it,k\neq 1}$, companionship C_{it}, place P_{it}, location L_{it}, and meteorological conditions M_{it}. As seen, our coefficient remains stable, being bound between -3.1 in our model without time-varying controls (Column 2) and -3.6 in our full model (Column 3). It varies by less than 14%. Recall that respondents have the option to select two residual activities if none of the offered fits their current as well as one residual location. Unobservable activities and locations should be captured by these.

Implicit in our argument about coefficient stability is that coefficient movements are informative about the extent of unobservable selection. However, this is only the case if observables are correlated with unobservables, and as Oster (2019) argues, both coefficient *and* R Squared movements should be taken into account to make meaningful statements about unobservable selection.

In particular, Oster (2019) develops a bounding argument to make statements based on two parameters: the maximum attainable R Squared (R^2_{max}) and the degree of selection on unobservables relative to selection on observables (γ). First, setting $\gamma = 1$ (unobservables are as important as observables) and assuming that $R^2_{max} = 1.3 \times R^2$ (as per Oster (2019)'s suggestion based on published randomised controlled trials in economics), our coefficient δ changes from originally -3.6 to now -3.7, which is only a minor change and, if anything, bounds our coefficient further away from zero.[28] Second, we calculate the γ that would be necessary to turn our coefficient δ into zero. Assuming again that $R^2_{max} = 1.3 \times R^2$, we obtain $\gamma = -90.3$. This implies that selection on unobservables must be *substantially* more important than selection on observables to turn δ into zero, specifically 90 times more important than our time-varying controls X_{it}, region and time fixed effects r and T, and individual fixed effects u_i. This is rather unlikely. We conclude that selection on unobservables and potential omitted variable bias is of little concern.

5.2 Income

Next, we look at our estimate of the effect of income on happiness. Our coefficient for log annual gross household income (i.e. 0.9) comes from an auxiliary regression using our own data. In particular, we regress happiness on log annual gross household income, equivalised, from all sources using the same model as in Equation 2, with two exceptions: first, we include an additional set of time-invariant individual and household controls (age, marital status, health, and whether there are children in the household). Second, we exclude individual fixed effects. This is because respondents are asked about income only once (in the intake survey, before being asking about their momentary happiness and activities, to avoid priming).[29]

Appendix Table A4 shows our results. Column 1 includes no controls, whereas Columns 2 to 4 successively add region and time fixed effects r and T (Column 2); time-varying controls X_{it}, including activities A_{it}, companionship C_{it}, place P_{it}, location L_{it}, and meteorological

[28] Oster (2019) considers $\gamma = 1$ to be a sensible value, as observables should, in theory, be at least as important as unobservables.

[29] Our measure of annual gross household income is provided in bands. We take the midpoint of each of the twelve bands and equivalise the resulting household income using the standard OECD formula, by dividing it by (1 for the first adult + 0.5 for each subsequent adult + 0.3 for each child in the household).

conditions M_{it} (Column 3); and time-invariant individual and household controls X_i (Column 4). Moreover, Column 5 replaces equivalised with non-equivalised income. Finally, Column 6 uses a filtered fixed-effects model, an approach that estimates individual fixed effects alongside time-invariant controls in a two-step procedure (Pesharan and Zhou, 2016). As seen, our coefficient remains stable and robust to various parametrisations and specifications, being bound between 1.4 and 0.9, with 0.9 for equivalised income in our full model (Column 4) as our preferred coefficient. Note that it makes little difference whether we use equivalised or non-equivalised income.

Next, Appendix Table A5 compares our coefficients (equivalised in Columns 1a and 1b as well as non-equivalised in Columns 2a and 2b) with selected coefficients from the literature.[30] To our knowledge, the only directly comparable study to ours in terms of data and methods is Killingsworth (2021): like us, the author conducts an experience-sampling study ("Track Your Happiness"), this time in the US, reporting a raw correlation between happiness and log annual gross household income from all sources of 1.1 in a restricted sample of employed, working-age US adults with a minimum annual income of $\$10,000$ (Column 3a), reducing to 0.7 when controlling for age, gender, marital status, and education (Column 3b). The raw correlation for an unrestricted sample is 0.9 (Column 4a), a partial correlation for that sample is not reported.[31] The only directly comparable study to ours, therefore, points towards a coefficient for income that is similar to ours.

5.3 Estimation

So far, we have used a linear model. In a recent paper, Bond and Lang (2019), who look at dependent variables of wellbeing with a limited number of categories (e.g. zero-to-ten Likert scales), show that results from ordered models, which typically focus on mean levels of wellbeing in different groups, may be reversed.

This is unlikely to be an issue in our case, as our dependent variable ranges *continuously*

[30] While several studies attempt to estimate the effect of income on life satisfaction (a global, evaluative measure of wellbeing) (Stevenson et al., 2008; Kahneman and Deaton, 2010; Sacks et al., 2010; Clark et al., 2018; De Neve et al., 2018; Lindqvist et al., 2020), few to none estimate the effect of income on happiness (a momentary, experiential measure) due to a lack of data. Kahneman and Deaton (2010) compare effects between life satisfaction and happiness, but their measure of happiness is captured retrospectively by surveys, asking respondents to reflect on their happiness on the previous day, which may not constitute a genuine momentary experience.

[31] While Killingsworth (2021)'s measure of household income is similar to ours (it has slightly more bands to capture high-income individuals), the measure of happiness is different. In particular, it asks respondents: "How do you feel right now?", with answers ranging from "Very bad" to "Very good".

(limited only by the pixel resolution of the smartphone) from zero to 100. Nevertheless, we follow Bloem and Oswald (2021) and conduct a *Dichotomous-Around-the-Median (DAM)* test, which uses information only on direction within ordered data and deliberately discards potentially unreliable statistical information. In particular, the test requires us to dichotomise our dependent variable such that it is one for responses above the median, and zero otherwise; to standardise it (to a mean of zero and a standard deviation of one, i.e. a z-score); and to re-estimate Equation 2 using this modified dependent variable. The coefficients are then compared to those from our original model (using our original dependent variable, likewise standardised). Appendix Table A6 shows that δ remains significant, strong negative, and, importantly, is similar across models.[32]

5.4 External Validity

Finally, we check our data for external validity, by comparing the individual and household characteristics in our intake survey with those in the nationally representative UK Household Longitudinal Study ("Understanding Society"), and the activities in our experience-sampling survey with those in the nationally representative UK Time Use Survey (UKTUS). For each comparison, we generate variables in the external data that are as similar as possible to ours, and then calculate normalised differences in means.[33] To maximise comparability, we restrict Understanding Society to Wave 2 (the years 2010 to 2011, when most respondents selected into our study) and use cross-sectional weights to achieve representativeness. The UKTUS is available for the years 2014 and 2015 only. Taken together, both visual inspection and normalised differences suggest that our data score well in terms of external validity.

Appendix Table A7 shows means and standard deviations for individual and household characteristics by sample as well as normalised differences in means between them. As seen, only few normalised differences exceed 0.25, which Imbens and Wooldridge (2009) suggest as a threshold above which covariates are considered unbalanced. Perhaps unsurprisingly, respondents in our sample tend to be younger, less likely to be married, more likely to be employed or self-employed, and less likely to be retired, compared to the UK general population.

[32]This remains the case if we dichotomise and standardise not globally but per individual (results available upon request).

[33]Contrary to simple differences, normalised differences are scale-free, i.e. independent of sample size, and hence more informative about the degree of covariate imbalance, if any, between large samples (Imbens and Rubin, 2015). The normalised difference is calculated as $\Delta x = (\bar{x_t} - \bar{x_c})/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x_t}$ and $\bar{x_c}$ is the sample mean of variable x in the first and second group, respectively. σ^2 denotes the respective variance (Imbens and Wooldridge, 2009; Imbens and Rubin, 2015).

They are, however, relatively similar when it comes to gender, self-assessed health, annual gross household income, and household composition, including the number of adults and children in the household. They are also relatively similar with respect to their geographical distribution across the UK.

Similarly, Appendix Table A8a shows means and standard deviations for activities on weekdays (Monday to Friday) by sample as well as normalised differences in means between them. Appendix Table A8b shows the same for weekends (Saturday and Sunday) and holidays.[34] Here, none of the normalised differences exceed 0.25. The similarity between activities in our data and those in the external data also suggests that selection into the reporting of activities, i.e. $R(.)$, which may yield potentially biased response shares s, is of little concern.

6 Discussion and Conclusion

We have proposed a new method to value time: *experiential valuation* based on experience sampling. While we are the first to value time, or indeed anything else, using hedonic experiences in real-time, the idea behind this approach is old, going all the way back to early economist Francis Y. Edgeworth.

Inspired by him, we used a smartphone app that during the years 2010 to 2016 randomly sampled the momentary happiness and activities of $30,928$ UK residents ($N = 2,234,753$) longitudinally as they went about their daily lives. Exploiting the randomised timing of surveys for identification, we estimated the VOT for 42 daily activities, by subtracting from the income equivalent of each activity the time use-weighted average income equivalent of all the other activities (as counterfactual). Our models looked at within-individual variation, controlling for other activities respondents may be simultaneously engaged in (multi-tasking), where they currently are, whom they are with, meteorological conditions, and region and time fixed effects.

We arrived at a VOT of £-12 (\$$-15$) per hour of commuting and £-24 (\$$-31$) per hour of waiting during commuting (e.g. due to congestion). These figures can be directly used in cost-benefit analyses to quantify the benefits associated with investments into congestion-reducing infrastructure. INRIX (2019b), for example, estimate the costs of being stuck in traffic for 115 hours per year to the average road user in the UK to be £$1,168$ (\$$1,483$). Using our

[34] We differentiate weekdays from weekends as the UKTUS oversamples weekends.

VOT of £-24 (\$ $-$ 31) per hour, we estimate these costs to be more than twice as much, namely: £$2,760$ (\$$3,505$). Beyond averages, we also documented substantial heterogeneity in our VOT estimates, in that women and low-income households suffer substantially more from commuting and congestion, and hence would benefit relatively more. We found similar heterogeneity for many other activities, highlighting the importance of using VOT estimates specific to target groups in welfare analyses. Our VOT of £-12 (\$$-15$) per hour of commuting, in absolute terms, is similar to Goldszmidt et al. (2020), who estimate a VOT of \$19 in the US in 2020. This suggests that hedonic experiences yield similar (though not identical) results as observed behaviour.

Our method can be used as an alternative (or complement) to hedonic pricing or using accounts of life satisfaction in non-market valuation, an approach that has become accepted in the public and environmental economics literature (van Praag and Baarsma, 2005; Luechinger, 2009; Luechinger and Raschky, 2009; Maddison and Rehdanz, 2011; Levinson, 2012; Krekel and Zerrahn, 2017; von Möllendorff and Welsch, 2017; Dolan et al., 2019, 2021; Krekel et al., 2021; Goebel et al., 2022) as well as in public policy. In particular, hedonic experiences in real-time can be used to value non-market goods and services for which no complementary markets exist or which are too granular to be captured by life satisfaction, such as infrequent time spent in various activities (e.g. sports or cultural activities) or places (e.g. green spaces or historical sites), but that are nevertheless of policy interest as they provide social value.[35] For example, spending one hour doing sports or exercise can be valued at £17 (\$21), one hour at a theatre, dance, or concert at 16 (\$20), and one hour in an exhibition, museum, or library at £11 (\$14). The same is true for household production tasks, such as providing care or help for other adults (£-18, \$ $-$ 23) or children (£4, \$5). Our method, therefore, enables statistical agencies to paint a more complete picture of social value in national accounts, better including, for example, household production. Importantly, it is relatively cheap and easy to implement, allowing for a uniform methodology to calculate the VOT for most activities in people's lives.

Our study has several limitations. When it comes to internal validity, we are not able to

[35]For example, HM Treasury in the UK allows the use of a *Wellbeing-Year (WELLBY)* as a measure of benefit in cost-benefit analyses, defined as one point of life satisfaction on a zero-to-ten Likert scale for one individual for one year (Frijters et al., 2020; Frijters and Krekel, 2021; Frijters et al., 2024). It is valued at £$15,258$ (\$$19,378$) (in 2023 prices) (HM Treasury, 2021b,a). As a complement, one can think of an experiential measure, e.g. a *Wellbeing-Hour*, which can be defined as one point of happiness in real-time on a zero-to-100 scale for one individual for one hour. As discussed in Section 4.1, it can be valued at £2.5 (\$3.2).

formally claim causality, which would require an exogenous source of variation. In fact, to estimate the VOT for 42 daily activities, we would have to set up 42 (quasi-)experiments with potentially 42 activity-specific sources of variation, a daunting task. At the same time, focusing on one activity only may help with causality but may come at the cost of generalisability. The randomised timing of our surveys, however, aims to ensure that respondents do not select into surveys based on their current circumstances. Moreover, our coefficients remain stable regardless of whether or not we include time-varying controls as well as region and time fixed effects. Finally, a bounding argument in line with Oster (2019) shows that unobservables and potential omitted variable bias are of little concern.

Relative to conventional time use surveys, which ask respondents retrospectively about their feelings and activities using diaries, experience sampling may be more subject to reactivity, in that the very act of asking respondents about their momentary feelings may affect their feelings. We expect this to be a minor issue, though, as respondents in our sample are asked repeatedly and the novelty of being asked is likely to wear off after a while. Individuals may also derive pleasure or displeasure from anticipating or remembering certain activities, or may adapt to activities once they have been doing them for some time. Our method is only able to capture *current* activities, which is a potential limitation. Finally, due to the randomised timing of surveys, our calculated VOT can be interpreted as the average VOT, yet policy-makers may be interested in the marginal. For the average and marginal to coincide, we need to assume that the hedonic experiences of activities are independent of their durations, which for some activities may be true but for others not – another limitation.

When it comes to external validity, respondents in our sample tend to be younger (and potentially more technologically savvy) than the UK general population. However, other individual and household characteristics in our intake survey compare well with those in nationally representative household data, and activities in our experience-sampling sample with those in nationally representative time use data in the UK, which suggests that external validity is high.

Measuring people's hedonic experiences in real-time gives us a rich and so far largely unexplored source of data, and using experiential valuation may help us put a price tag on most activities of people's lives, and so make them relevant for policy. It has the potential to value other intangibles too.

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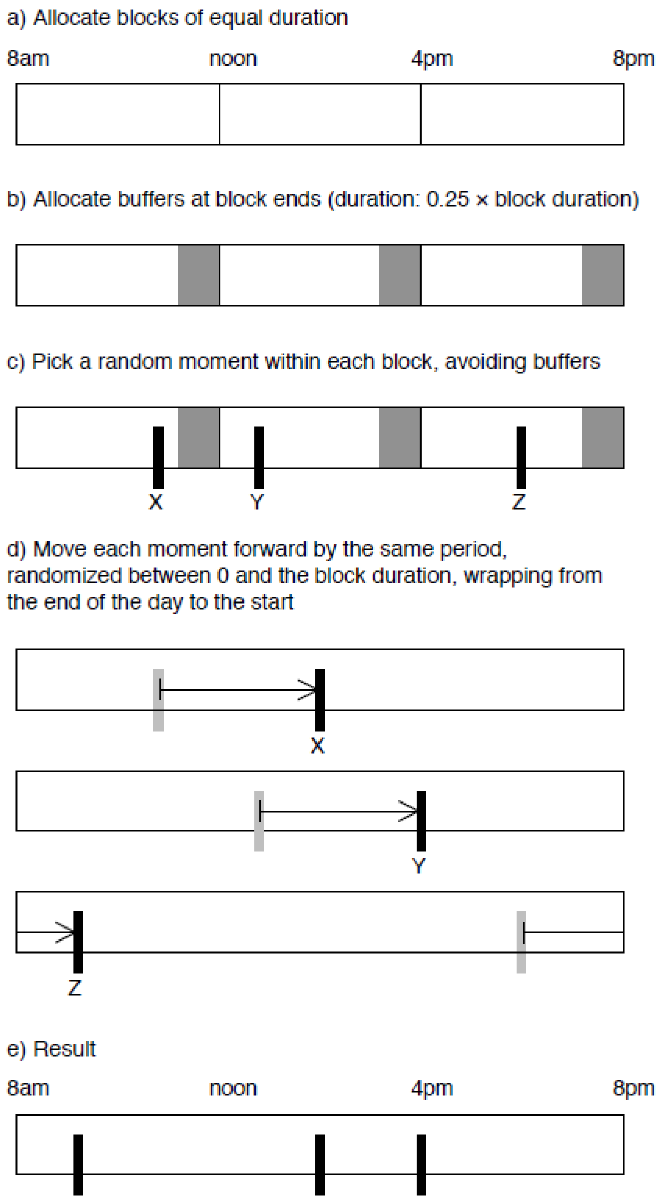
Figure 1: Smartphone App – Randomisation Algorithm



Notes: The algorithm has four steps: first, it allocates three blocks of equal duration between the daily start and end time. Second, it allocates a buffer at the end of each block (of 0.25× the block's duration) to avoid having two consecutive experience-sampling surveys too closely spaced in time. Third, it picks a random moment within each block, avoiding the block's buffer. Finally, it moves each randomly picked moment forward by the same duration, randomly chosen to be between zero and the block's full duration (including buffer), wrapping from the end of the day to its start, to reduce predictability while ensuring a uniform probability sample. *Sources:* Mappiness app, own illustration.

Table 1: Regression Results

k	*Activity* ($A_{it,k}$)	Happy (0-100) Coefficient	Standard Error	Response Share s_k
1	Waiting, Queueing	-3.61***	(0.14)	2.32%
2	Commuting, Travelling	-1.86***	(0.10)	8.99%
3	Working, Studying	-1.61***	(0.08)	24.98%
4	In Meeting, Seminar, Class	0.30***	(0.11)	2.83%
5	Cooking, Preparing Food	2.24***	(0.08)	4.32%
6	Housework, Chores, DIY	-0.53***	(0.08)	5.19%
7	Shopping, Running Errands	0.71***	(0.09)	3.01%
8	Admin, Finances, Organising	-1.27***	(0.12)	3.92%
9	Childcare, Playing With Children	2.77***	(0.14)	4.45%
10	Petcare, Playing With Pets	3.20***	(0.17)	1.88%
11	Care or Help for Adults	-3.85***	(0.62)	0.54%
12	Sleeping, Resting, Relaxing	0.93***	(0.07)	9.86%
13	Sick in Bed	-18.36***	(0.29)	1.53%
14	Meditating, Religious Activities	3.95***	(0.37)	0.31%
15	Washing, Dressing, Grooming	2.01***	(0.08)	3.68%
16	Talking, Chatting, Socialising	4.17***	(0.07)	14.93%
17	Intimacy, Making Love	12.66***	(0.26)	0.56%
18	Eating, Snacking	2.01***	(0.06)	9.82%
19	Drinking Tea or Coffee	1.38***	(0.06)	6.42%
20	Drinking Alcohol	3.61***	(0.09)	5.08%
21	Smoking	0.45**	(0.18)	1.32%
22	Texting, E-Mail, Social Media	0.92***	(0.08)	5.62%
23	Browsing the Internet	0.78***	(0.08)	5.13%
24	Watching TV, Film	2.28***	(0.06)	18.00%
25	Listening to Music	3.28***	(0.09)	6.27%
26	Listening to Speech or Podcast	1.75***	(0.12)	2.09%
27	Reading	1.93***	(0.12)	3.30%
28	Theatre, Dance, Concert	6.55***	(0.25)	0.33%
29	Exhibition, Museum, Library	5.17***	(0.25)	0.23%
30	Match, Sporting Event	2.37***	(0.27)	0.60%
31	Walking, Hiking	2.40***	(0.14)	1.48%
32	Sports, Running, Exercise	6.72***	(0.15)	1.25%
33	Gardening, Allotment	4.84***	(0.24)	0.31%
34	Birdwatching, Nature Watching	4.56***	(0.33)	0.16%
35	Computer Games, Smart Phone Games	2.59***	(0.11)	2.82%
36	Hunting, Fishing	3.58***	(0.98)	0.02%
37	Other Games, Puzzles	2.70***	(0.21)	0.40%
38	Gambling, Betting	1.60**	(0.64)	0.07%
39	Hobbies, Arts, Crafts	5.14***	(0.21)	1.03%
40	Singing, Performing	6.00***	(0.28)	0.40%
41	Something Else	-1.54***	(0.17)	1.28%
42	Other	-3.59***	(0.51)	3.13%
	Company (C_{it})			
	Spouse, Partner, Girlfriend, or Boyfriend	3.68***	(0.09)	
	Children	0.45***	(0.12)	
	Other Family Members	0.84***	(0.08)	
	Colleagues, Classmates	-0.22**	(0.10)	
	Clients, Customers	1.11***	(0.23)	
	Friends	4.14***	(0.08)	

Table 1 Continued

Other People You Know	-0.56***	(0.13)
Place (P_{it})		
At Work	Reference Category	
At Home	2.79***	(0.09)
Elsewhere	0.18*	(0.10)
Location (L_{it})		
Indoors	Reference Category	
Outdoors	1.45***	(0.07)
In Vehicle	-2.43***	(0.11)
Meteorological Controls (M_{it})		
Air Temperature	Yes	
Wind Speed	Yes	
Precipitation	Yes	
Cloud Cover	Yes	
Sunshine	Yes	
Daylight	Yes	
Spatial Controls (r)		
Region Fixed Effects	Yes	
Temporal Controls (T)		
Holiday-Season Fixed Effects	Yes	
Hour-of-Day Fixed Effects	Yes	
Day-of-Week Fixed Effects	Yes	
Month Fixed Effects	Yes	
Year Fixed Effects	Yes	
Individual Fixed Effects	Yes	
Constant	Yes	
Number of Individuals	30,928	
Number of Observations	2,234,753	
Adjusted R Squared	0.44	
Adjusted R Squared Within	0.11	
F-Test	190.45	

Robust standard errors clustered two-way at the region and respondent levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Individual fixed-effects regression of momentary happiness on momentary 42 activities (which can be multiple due to multitasking), 7 types of companionship (which can also be multiple), 3 types of places, 3 types of locations, and current meteorological conditions. We also include spatial and temporal controls, i.e. $8,925$ regional fixed effects at the Middle Layer Super Output Area (MSOA) level and holiday-season, hour-of-day, day-of-week, month, and year fixed effects. See Equation 2 for the model. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table 2: Value of Time (VOT) for 42 Daily Activities

k	*Activity* ($A_{it,k}$)	Happy (0-100) Coefficient (1)	Monetary Equivalent (£, 60 Minutes) (2)	Response Share s_k (3)	s-Weighted Average of Column 2 Excluding k (4)	VOT_k (£, 60 Minutes) (5) = (2) - (4)	VOT_k (£, 60 Minutes) (6) = (5) in 2023 Prices
1	Waiting, Queueing	-3.61	-8.94	0.02	4.29	-13.24	-17.18
2	Commuting, Travelling	-1.86	-4.61	0.09	4.50	-9.11	-11.83
3	Working, Studying	-1.61	-3.99	0.25	5.08	-9.08	-11.78
4	In Meeting, Seminar, Class	0.30	0.75	0.03	4.07	-3.31	-4.30
5	Cooking, Preparing Food	2.24	5.55	0.04	3.85	1.70	2.20
6	Housework, Chores, DIY	-0.53	-1.31	0.05	4.16	-5.46	-7.09
7	Shopping, Running Errands	0.71	1.76	0.03	4.03	-2.28	-2.95
8	Admin, Finances, Organising	-1.27	-3.14	0.04	4.21	-7.35	-9.53
9	Childcare, Playing With Children	2.77	6.85	0.04	3.78	3.06	3.98
10	Petcare, Playing With Pets	3.20	7.92	0.02	3.94	3.98	5.16
11	Care or Help for Adults	-3.85	-9.54	0.01	4.14	-13.68	-17.75
12	Sleeping, Resting, Relaxing	0.93	2.29	0.10	3.86	-1.57	-2.04
13	Sick in Bed	-18.36	-45.44	0.02	4.78	-50.22	-65.17
14	Meditating, Religious Activities	3.95	9.78	0.00	4.06	5.72	7.42
15	Washing, Dressing, Grooming	2.01	4.98	0.04	3.90	1.08	1.40
16	Talking, Chatting, Socialising	4.17	10.32	0.15	2.55	7.77	10.08
17	Intimacy, Making Love	12.66	31.33	0.01	3.91	27.42	35.58
18	Eating, Snacking	2.01	4.99	0.10	3.60	1.39	1.80
19	Drinking Tea or Coffee	1.38	3.42	0.06	3.87	-0.44	-0.57
20	Drinking Alcohol	3.61	8.93	0.05	3.63	5.30	6.87
21	Smoking	0.45	1.11	0.01	4.07	-2.96	-3.84
22	Texting, E-Mail, Social Media	0.92	2.27	0.06	3.96	-1.69	-2.19
23	Browsing the Internet	0.78	1.94	0.05	3.99	-2.05	-2.66
24	Watching TV, Film	2.28	5.64	0.18	3.07	2.57	3.34
25	Listening to Music	3.28	8.12	0.06	3.58	4.54	5.90
26	Listening to Speech or Podcast	1.75	4.32	0.02	4.00	0.32	0.42
27	Reading	1.93	4.79	0.03	3.93	0.86	1.11
28	Theatre, Dance, Concert	6.55	16.21	0.00	4.03	12.17	15.80
29	Exhibition, Museum, Library	5.17	12.79	0.00	4.06	8.73	11.33
30	Match, Sporting Event	2.37	5.86	0.01	4.05	1.81	2.35
31	Walking, Hiking	2.40	5.94	0.01	4.00	1.94	2.51
32	Sports, Running, Exercise	6.72	16.62	0.01	3.88	12.74	16.53
33	Gardening, Allotment	4.84	11.98	0.00	4.05	7.93	10.29
34	Birdwatching, Nature Watching	4.56	11.29	0.00	4.07	7.22	9.37
35	Computer Games, Smart Phone Games	2.59	6.40	0.03	3.91	2.50	3.24
36	Hunting, Fishing	3.58	8.87	0.00	4.09	4.78	6.21
37	Other Games, Puzzles	2.70	6.68	0.00	4.06	2.62	3.40
38	Gambling, Betting	1.60	3.96	0.00	4.08	-0.12	-0.16
39	Hobbies, Arts, Crafts	5.14	12.71	0.01	3.96	8.76	11.36

Table 2 Continued

k	*Activity* $(A_{it,k})$	Happy (0-100) Coefficient (1)	Monetary Equivalent (£, 60 Minutes) (2)	Response Share s_k (3)	s_k-Weighted Average of Column 2 Excluding k (4)	VOT_k (£, 60 Minutes) (5) = (2) - (4)	VOT_k (£, 60 Minutes) (6) = (5) in 2023 Prices
40	Singing, Performing	6.00	14.84	0.00	4.03	10.81	14.02
41	Something Else	-1.54	-3.82	0.01	4.14	-7.95	-10.32
42	Other	-3.59	-8.87	0.03	4.36	-13.24	-17.18

Notes: VOT_k is the monetary value of spending one hour in activity $A_{it,k}$ as opposed to doing something else. To obtain $VOT_{k=1}$, for example, we first calculate the marginal rate of substitution $MRS_{k=1}$ between activity $A_{it,k=1}$ and income to arrive at an income equivalent of the activity. Then, we subtract from that income equivalent the average income equivalent of the $k = \{2, 3, 4, ...42\}$ other daily activities, weighted by their response share s_k (as counterfactual). We evaluate $MRS_{k=1}$ at the average annual gross household income in the UK in 2016 (the last year during our observation period), scaled to £/hour. See Equation 3 for the calculation. See Equation 2 for the model. Table 1 shows the regression results from which the coefficients are obtained. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table 3: Interactions: Value of Time (VOT) for Waiting in 41 Daily Activities

k	*Activity* ($A_{it,k}$)	Happy (0-100) Coefficients $A_{it,k}$ (1)	$A_{it,k=1}$ (2)	$A_{it,k} \times A_{it,k=1}$ (3)	(4) = (1) + (2) + (3)	Monetary Equivalent (£, 60 Minutes) of Column 4 (5)	s-Weighted Average of Table 3 Column 2 Excluding k (6)	$VOT_{k=1,k}$ (£, 60 Minutes) (7) = (5) - (6)	$VOT_{k=1,k}$ (£, 60 Minutes) (8) = (7) in 2023 Prices
1	Waiting, Queueing	-	-	-	-	-	-	-	-
2	Commuting, Travelling	-1.97	-4.43	0.70	-5.71	-14.12	4.50	-18.62	-24.16
3	Working, Studying	-1.68	-4.43	1.33	-4.78	-11.83	5.08	-16.91	-21.94
4	In Meeting, Seminar, Class	0.27	-4.43	-0.53	-4.69	-11.60	4.07	-15.67	-20.33
5	Cooking, Preparing Food	2.20	-4.43	0.75	-1.48	-3.65	3.85	-7.50	-9.73
6	Housework, Chores, DIY	-0.58	-4.43	0.98	-4.03	-9.98	4.16	-14.13	-18.34
7	Shopping, Running Errands	0.61	-4.43	0.71	-3.12	-7.71	4.03	-11.75	-15.24
8	Admin, Finances, Organising	-1.33	-4.43	1.06	-4.69	-11.62	4.21	-15.83	-20.53
9	Childcare, Playing With Children	2.74	-4.43	0.21	-1.47	-3.65	3.78	-7.43	-9.64
10	Petcare, Playing With Pets	3.20	-4.43	-0.94	-2.17	-5.37	3.94	-9.31	-12.08
11	Care or Help for Adults	-4.10	-4.43	0.34	-8.19	-20.27	4.14	-24.41	-31.68
12	Sleeping, Resting, Relaxing	0.87	-4.43	1.78	-1.78	-4.40	3.86	-8.27	-10.73
13	Sick in Bed	-18.56	-4.43	10.85	-12.14	-30.04	4.78	-34.82	-45.18
14	Meditating, Religious Activities	3.98	-4.43	-3.45	-3.89	-9.64	4.06	-13.69	-17.77
15	Washing, Dressing, Grooming	1.94	-4.43	0.96	-1.53	-3.79	3.90	-7.70	-9.99
16	Talking, Chatting, Socialising	4.12	-4.43	1.56	1.25	3.10	2.55	0.55	0.71
17	Intimacy, Making Love	12.66	-4.43	-3.94	4.30	10.63	3.91	6.72	8.72
18	Eating, Snacking	1.98	-4.43	0.82	-1.63	-4.02	3.60	-7.62	-9.89
19	Drinking Tea or Coffee	1.37	-4.43	0.44	-2.62	-6.48	3.87	-10.35	-13.43
20	Drinking Alcohol	3.59	-4.43	0.88	0.04	0.11	3.63	-3.53	-4.58
21	Smoking	0.40	-4.43	1.80	-2.22	-5.50	4.07	-9.57	-12.42
22	Texting, E-Mail, Social Media	0.88	-4.43	0.65	-2.90	-7.16	3.96	-11.12	-14.43
23	Browsing the Internet	0.75	-4.43	0.84	-2.84	-7.03	3.99	-11.02	-14.30
24	Watching TV, Film	2.26	-4.43	-0.66	-2.83	-7.01	3.07	-10.09	-13.09
25	Listening to Music	3.28	-4.43	-0.29	-1.43	-3.55	3.58	-7.13	-9.25
26	Listening to Speech or Podcast	1.71	-4.43	0.40	-2.31	-5.72	4.00	-9.72	-12.61
27	Reading	1.90	-4.43	-0.07	-2.60	-6.44	3.93	-10.37	-13.45
28	Theatre, Dance, Concert	6.47	-4.43	1.01	3.05	7.54	4.03	3.50	4.55
29	Exhibition, Museum, Library	5.15	-4.43	-0.84	-0.12	-0.29	4.06	-4.35	-5.64
30	Match, Sporting Event	2.30	-4.43	0.57	-1.56	-3.85	4.05	-7.91	-10.26
31	Walking, Hiking	2.38	-4.43	-2.34	-4.39	-10.86	4.00	-14.86	-19.28
32	Sports, Running, Exercise	6.66	-4.43	-0.43	1.81	4.47	3.88	0.59	0.76
33	Gardening, Allotment	4.79	-4.43	-0.47	-0.12	-0.29	4.05	-4.33	-5.62
34	Birdwatching, Nature Watching	4.45	-4.43	1.87	1.89	4.68	4.07	0.61	0.79
35	Computer Games, Smart Phone Games	2.59	-4.43	-1.62	-3.46	-8.57	3.91	-12.48	-16.19
36	Hunting, Fishing	3.54	-4.43	-1.02	-1.91	-4.73	4.09	-8.81	-11.43
37	Other Games, Puzzles	2.71	-4.43	-1.29	-3.02	-7.46	4.06	-11.52	-14.95
38	Gambling, Betting	1.70	-4.43	-4.54	-7.27	-17.98	4.08	-22.07	-28.63
39	Hobbies, Arts, Crafts	5.09	-4.43	0.96	1.62	4.00	3.96	0.05	0.06

Table 3 Continued

k	*Activity* ($A_{it,k}$)	Happy (0-100) Coefficients $A_{it,k}$ (1)	$A_{it,k=1}$ (2)	$A_{it,k} \times A_{it,k=1}$ (3)	(4) = (1) + (2) + (3)	Monetary Equivalent (£, 60 Minutes) of Column 4 (5)	s_k-Weighted Average of Table 3 Column 2 Excluding k (6)	$VOT_{k=1,k}$ (£, 60 Minutes) (7) = (5) - (6)	$VOT_{k=1,k}$ (£, 60 Minutes) (8) = (7) in 2023 Prices
40	Singing, Performing	6.01	-4.43	-3.48	-1.90	-4.70	4.03	-8.72	-11.32
41	Something Else	-1.51	-4.43	-3.97	-9.91	-24.52	4.14	-28.65	-37.18
42	Other	-3.63	-4.43	-0.07	-8.13	-20.11	4.36	-24.48	-31.76

Notes: $VOT_{k=1,k}$ is the monetary value of spending one hour *waiting or queueing* in activity k as opposed to doing something else. To obtain $VOT_{k=1,2}$, for example, we first re-estimate Equation 2 including an interaction between $A_{it,k=1}$ and $A_{it,k=2}$, and then calculate $VOT_{k=1,2}$ in the same way as in Equation 3. That is, we first calculate the marginal rate of substitution $MRS_{k=1,2}$ between the interaction of $A_{it,k=1}$ with $A_{it,k=2}$ and income to arrive at an income equivalent of the interaction. Then, we subtract from that income equivalent the average income equivalent of the $k = \{2, 3, 4, ...42\}$ other daily activities, weighted by their response share s_k (as counterfactual). We evaluate $MRS_{k=1,2}$ at the average annual gross household income in the UK in 2016 (the last year during our observation period), scaled to £/hour. See Equation 5 for the calculation. See Section 2 for a description of the data.

Source: Mappiness data, 2010 to 2016, own calculations.

Table 4a: Heterogeneity: Value of Time (VOT) for 42 Daily Activities and Interactions

		VOT_k / $VOT_{k=1,k}$ (£, 60 Minutes, 2023 Prices)									
		Average		Female		Male		Low Income		High Income	
k	Activity		With Waiting		With Waiting		With Waiting		With Waiting		With Waiting
1	Waiting, Queueing	-17.18	-	-19.02	-	-15.45	-	-18.84	-	-14.71	-
2	Commuting, Travelling	-11.83	-24.16	-13.47	-26.87	-10.14	-21.19	-12.50	-26.19	-11.62	-21.02
3	Working, Studying	-11.78	-21.94	-12.77	-22.46	-10.69	-21.03	-12.08	-23.47	-11.41	-21.50
4	In Meeting, Seminar, Class	-4.30	-20.33	-5.58	-20.90	-3.43	-18.93	-4.21	-20.16	-4.85	-20.10
5	Cooking, Preparing Food	2.20	-9.73	2.57	-9.95	1.54	-10.13	0.37	-14.54	2.91	-5.34
6	Housework, Chores, DIY	-7.09	-18.34	-7.25	-21.20	-6.93	-15.59	-8.11	-22.83	-5.76	-10.36
7	Shopping, Running Errands	-2.95	-15.24	-2.92	-15.23	-3.47	-15.18	-2.87	-13.27	-2.60	-14.36
8	Admin, Finances, Organising	-9.53	-20.53	-9.98	-25.27	-9.05	-17.27	-12.45	-25.04	-7.68	-16.90
9	Childcare, Playing With Children	3.98	-9.64	1.47	-11.11	6.18	-9.60	3.07	-6.02	5.38	-9.42
10	Petcare, Playing With Pets	5.16	-12.08	5.48	-12.49	4.58	-9.63	4.22	-21.61	5.83	-6.06
11	Care or Help for Adults	-17.75	-31.68	-19.58	-42.51	-17.32	-32.68	-19.47	-28.86	-17.27	-27.44
12	Sleeping, Resting, Relaxing	-2.04	-10.73	-1.24	-9.23	-3.09	-11.74	-3.75	-12.44	-0.74	-2.66
13	Sick in Bed	-65.17	-45.18	-65.47	-67.23	-65.48	-39.42	-65.43	-64.97	-61.16	-32.01
14	Meditating, Religious Activities	7.42	-17.77	9.71	-15.84	5.23	-20.70	9.06	-19.67	9.78	-15.12
15	Washing, Dressing, Grooming	1.40	-9.99	2.02	-11.40	0.48	-9.64	1.57	-7.78	1.29	-12.67
16	Talking, Chatting, Socialising	10.08	0.71	11.13	2.23	8.39	-0.60	10.27	2.21	9.52	-1.82
17	Intimacy, Making Love	35.58	8.72	37.87	2.03	33.25	10.68	36.77	21.37	33.21	-4.68
18	Eating, Snacking	1.80	-9.89	0.97	-12.07	2.45	-7.45	0.77	-12.79	2.51	-6.95
19	Drinking Tea or Coffee	-0.57	-13.43	-1.27	-15.85	-0.15	-10.62	-1.04	-18.95	0.11	-11.29
20	Drinking Alcohol	6.87	-4.58	6.08	-6.07	7.78	-2.57	7.50	-0.80	6.46	-4.87
21	Smoking	-3.84	-12.42	-5.65	-14.30	-2.26	-9.76	-5.11	-9.48	-3.31	-9.60
22	Texting, E-Mail, Social Media	-2.19	-14.43	-2.57	-16.11	-1.88	-12.89	-4.12	-17.21	-1.10	-11.13
23	Browsing the Internet	-2.66	-14.30	-3.66	-15.75	-1.97	-13.46	-4.29	-16.66	-1.53	-10.85
24	Watching TV, Film	3.34	-13.09	3.20	-12.53	3.28	-13.11	2.33	-12.92	3.62	-17.32
25	Listening to Music	5.90	-9.25	5.52	-10.81	5.92	-8.14	5.84	-9.68	6.12	-11.06
26	Listening to Speech or Podcast	0.42	-12.61	-0.32	-12.95	0.99	-12.84	0.16	-12.97	1.53	-12.29
27	Reading	1.11	-13.45	2.02	-14.74	-0.52	-13.31	0.80	-14.21	1.83	-14.61
28	Theatre, Dance, Concert	15.80	4.55	16.82	12.83	14.18	-0.83	15.28	7.40	16.69	3.10
29	Exhibition, Museum, Library	11.33	-5.64	12.90	2.43	9.05	-13.14	10.81	-11.05	11.28	-2.74
30	Match, Sporting Event	2.35	-10.26	3.22	3.40	2.70	-12.84	2.52	-8.20	3.46	-10.09
31	Walking, Hiking	2.51	-19.28	2.51	-15.08	2.47	-19.44	-0.23	-28.97	4.06	-17.13
32	Sports, Running, Exercise	16.53	0.76	17.65	6.81	15.90	-0.44	15.22	-5.28	18.10	1.70
33	Gardening, Allotment	10.29	-5.62	11.67	-17.05	8.88	4.31	8.09	-5.71	11.12	1.69
34	Birdwatching, Nature Watching	9.37	0.79	7.97	-6.06	9.90	1.33	9.12	-21.87	10.39	0.69
35	Computer Games, Smart Phone Games	3.24	-16.19	-1.46	-23.00	6.14	-11.36	2.87	-19.36	2.53	-15.19
36	Hunting, Fishing	6.21	-11.43	6.58	-28.58	7.36	22.10	2.35	-4.27	7.94	-5.70
37	Other Games, Puzzles	3.40	-14.95	1.27	-16.81	4.22	-15.08	1.09	-8.42	2.96	-13.08
38	Gambling, Betting	-0.16	-28.63	2.42	-29.85	-0.73	-26.45	2.28	-28.48	-3.71	-48.23
39	Hobbies, Arts, Crafts	11.36	0.06	10.96	-9.28	11.35	3.74	10.73	-8.76	12.09	7.88
40	Singing, Performing	14.02	-11.32	15.21	-12.65	12.38	-14.06	14.93	-17.02	13.64	-13.87
41	Something Else	-10.32	-37.18	-12.75	-43.05	-8.80	-32.76	-12.78	-34.92	-6.82	-36.70
42	Other	-17.18	-31.76	-20.74	-34.22	-12.07	-28.35	-18.94	-32.88	-14.28	-31.42

Notes: VOT_k is the monetary value of spending one hour in activity $A_{it,k}$ as opposed to doing something else, $VOT_{k=1,k}$ the monetary value of spending one hour *waiting or queueing* in activity k as opposed to doing something else. See Tables 2 and 3 for the average values and how they are calculated. The heterogeneous values are calculated by running the same regressions as for the average values (Equations 2 and 4), and conducting the same calculations (Equations 3 and 5), using sub-samples split by gender; household income (lowest and highest quartile); time of day (morning, afternoon, and evening); and day of week (weekday and weekend). See Section 2 for a description of the data.

Source: Mappiness data, 2010 to 2016, own calculations.

Table 4b: Heterogeneity: Value of Time (VOT) for 42 Daily Activities and Interactions

		VOT_k / $VOT_{k=1,k}$ (£, 60 Minutes, 2023 Prices)									
		Morning		Afternoon		Evening		Weekday		Weekend	
k	Activity		With Waiting		With Waiting		With Waiting		With Waiting		With Waiting
1	Waiting, Queueing	-14.66	-	-16.15	-	-19.78	-	-16.01	-	-19.07	-
2	Commuting, Travelling	-9.92	-19.68	-8.79	-20.82	-16.40	-32.05	-10.30	-22.10	-13.06	-26.90
3	Working, Studying	-6.90	-15.23	-10.49	-21.28	-18.58	-28.51	-10.40	-20.20	-15.45	-27.26
4	In Meeting, Seminar, Class	-2.21	-14.80	-3.07	-19.81	-7.64	-18.47	-3.40	-19.42	-4.33	-17.49
5	Cooking, Preparing Food	2.57	-6.31	3.84	-10.53	-0.72	-11.87	2.87	-11.08	0.49	-7.65
6	Housework, Chores, DIY	-3.57	-13.20	-5.58	-15.67	-12.47	-26.53	-4.91	-15.00	-11.17	-25.01
7	Shopping, Running Errands	1.31	-11.92	-1.24	-12.91	-9.02	-19.83	-0.67	-12.33	-8.50	-20.78
8	Admin, Finances, Organising	-7.32	-17.01	-8.70	-19.86	-12.20	-23.18	-8.94	-20.06	-10.16	-19.08
9	Childcare, Playing With Children	6.36	-3.00	4.73	-8.21	-0.08	-19.74	5.28	-7.02	0.76	-14.32
10	Petcare, Playing With Pets	7.86	-4.51	6.40	-10.87	1.47	-15.81	7.13	-9.44	0.90	-15.82
11	Care or Help for Adults	-14.63	-31.99	-15.01	-29.48	-26.13	-31.21	-15.14	-29.42	-24.04	-33.49
12	Sleeping, Resting, Relaxing	0.16	-5.66	-1.02	-8.74	-3.68	-14.03	-0.98	-10.86	-4.86	-10.63
13	Sick in Bed	-61.07	-40.57	-64.03	-43.65	-70.12	-49.50	-63.30	-43.19	-67.82	-47.98
14	Meditating, Religious Activities	6.96	-17.16	8.20	-17.09	6.01	-13.83	11.28	-17.90	1.88	-18.83
15	Washing, Dressing, Grooming	1.67	-9.20	3.88	-5.10	0.21	-13.14	2.06	-7.58	-0.50	-12.98
16	Talking, Chatting, Socialising	12.45	2.99	11.66	2.30	5.88	-3.54	11.67	1.82	6.37	-1.32
17	Intimacy, Making Love	38.31	7.82	38.08	19.00	29.58	1.97	37.67	7.41	30.95	9.36
18	Eating, Snacking	1.88	-8.02	2.58	-6.89	-0.49	-13.13	3.15	-8.76	-1.21	-11.78
19	Drinking Tea or Coffee	1.18	-12.57	0.03	-12.60	-4.16	-14.33	0.94	-10.91	-3.88	-18.72
20	Drinking Alcohol	7.69	32.07	8.22	-2.54	4.19	-8.10	8.09	0.04	4.02	-10.85
21	Smoking	-4.84	-9.98	-4.69	-12.76	-5.25	-14.14	-2.88	-11.03	-6.44	-15.17
22	Texting, E-Mail, Social Media	-0.60	-12.63	-1.31	-12.53	-4.94	-17.33	-0.92	-13.15	-5.54	-17.66
23	Browsing the Internet	0.37	-9.43	-1.31	-14.18	-6.84	-18.92	-1.24	-13.90	-6.18	-14.71
24	Watching TV, Film	5.02	-4.89	3.51	-12.24	0.75	-16.78	4.50	-10.94	0.46	-16.89
25	Listening to Music	7.36	-5.78	7.04	-8.49	2.33	-11.89	6.95	-7.20	2.87	-13.33
26	Listening to Speech or Podcast	1.99	-7.07	0.88	-11.50	-1.24	-17.50	1.58	-10.47	-2.43	-17.29
27	Reading	3.31	-8.89	2.51	-12.74	-2.61	-15.79	2.21	-11.17	-1.27	-17.80
28	Theatre, Dance, Concert	18.60	11.38	14.64	4.00	11.18	1.32	18.49	6.96	10.16	-1.73
29	Exhibition, Museum, Library	13.62	-0.72	13.46	-5.56	4.70	-7.42	14.22	-2.22	5.43	-11.07
30	Match, Sporting Event	11.37	3.22	3.24	-11.17	-2.42	-13.36	4.41	-11.27	-1.16	-11.53
31	Walking, Hiking	3.86	-18.21	4.76	-19.54	-3.20	-18.26	3.20	-19.19	-0.30	-19.06
32	Sports, Running, Exercise	20.45	19.66	17.32	-0.89	12.01	-5.35	18.78	1.99	11.14	-1.25
33	Gardening, Allotment	10.60	-7.01	10.94	-15.23	8.29	-11.41	12.81	-1.46	5.39	-13.28
34	Birdwatching, Nature Watching	12.89	15.78	9.28	0.00	5.98	-12.81	12.53	-0.38	4.85	0.46
35	Computer Games, Smart Phone Games	4.02	-13.59	5.42	-13.99	-1.44	-22.68	4.66	-14.31	-0.43	-19.36
36	Hunting, Fishing	8.63	40.51	7.11	-27.29	3.95	-6.23	7.92	-45.49	0.41	-13.37
37	Other Games, Puzzles	5.55	-29.23	5.07	-20.46	-0.80	2.29	3.90	-19.58	1.14	-5.26
38	Gambling, Betting	-0.59	-50.32	-1.12	-35.99	-1.86	-13.74	-0.24	-15.17	-0.09	-41.44
39	Hobbies, Arts, Crafts	14.93	-3.78	13.75	0.54	6.27	1.54	12.85	2.44	7.45	-4.30
40	Singing, Performing	13.08	-11.89	15.42	-8.00	10.83	-20.46	15.53	-10.09	10.21	-10.38
41	Something Else	-5.38	-43.88	-8.42	-26.61	-16.20	-48.03	-10.47	-37.99	-10.87	-34.36
42	Other	-14.73	-30.74	-14.28	-26.73	-23.21	-38.13	-16.76	-32.29	-18.46	-29.74

Notes: VOT_k is the monetary value of spending one hour in activity $A_{it,k}$ as opposed to doing something else, $VOT_{k=1,k}$ the monetary value of spending one hour *waiting or queueing* in activity k as opposed to doing something else. See Tables 2 and 3 for the average values and how they are calculated. The heterogeneous values are calculated by running the same regressions as for the average values (Equations 2 and 4), and conducting the same calculations (Equations 3 and 5), using sub-samples split by gender; household income (lowest and highest quartile); time of day (morning, afternoon, and evening); and day of week (weekday and weekend). See Section 2 for a description of the data.

Source: Mappiness data, 2010 to 2016, own calculations.

Appendix

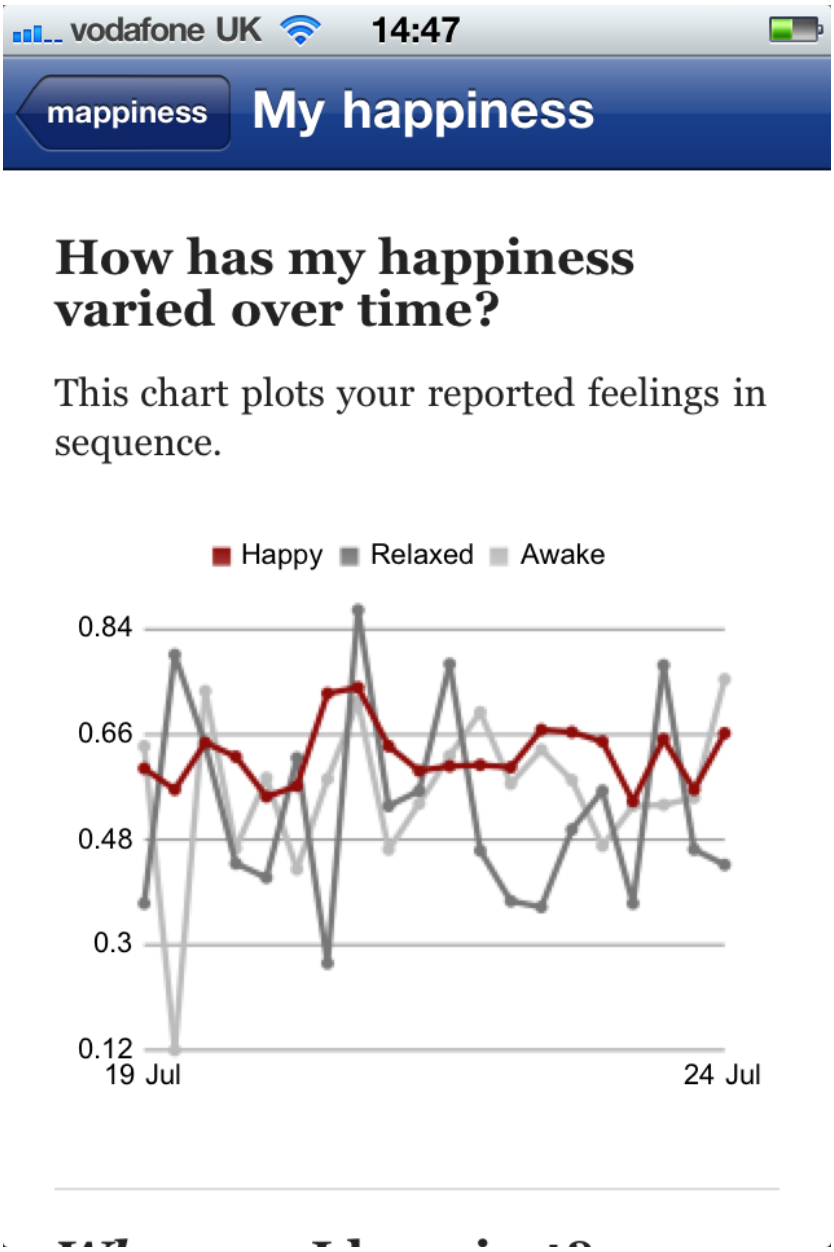
Figure A1: Smartphone App – User Interface

Sources: Mappiness app, screenshot.

Figure A2: Smartphone App – Experience-Sampling Survey

Sources: Mappiness app, screenshot.

Figure A3: Smartphone App – Personalised Feedback

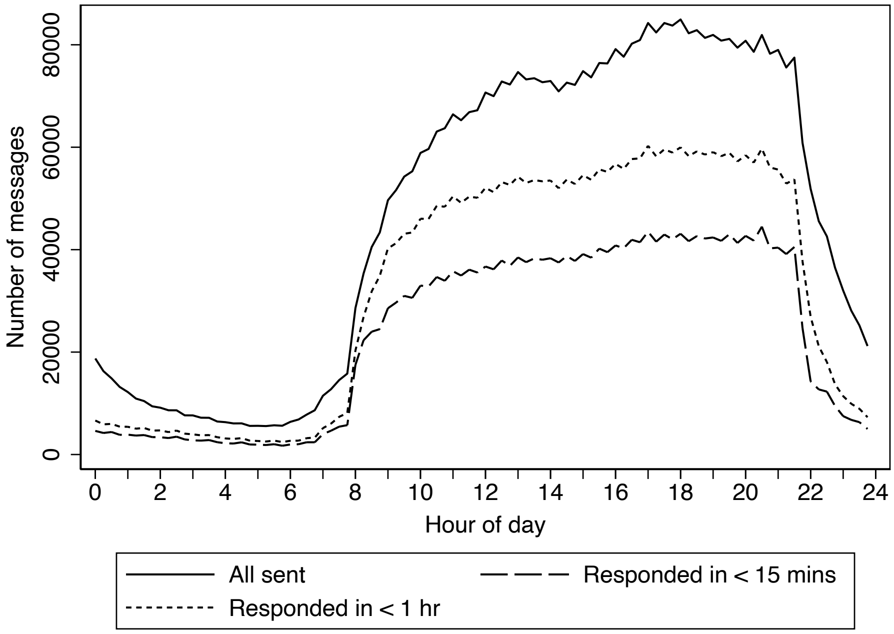


Sources: Mappiness app, screenshot.

Figure A4: Smartphone App – Settings

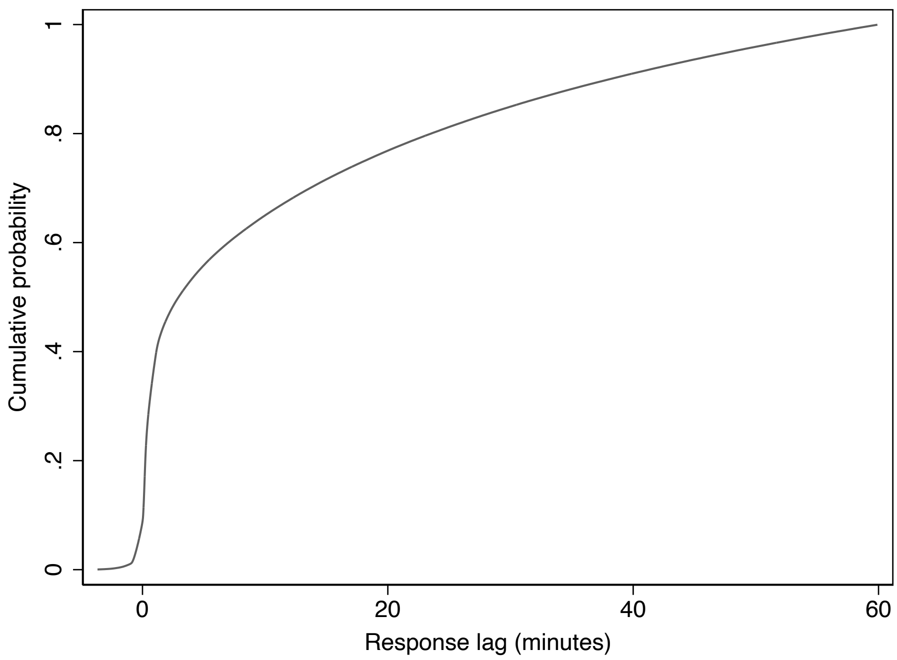
Sources: Mappiness app, screenshot.

Figure A5: Experience-Sampling Survey – Distribution of Responses by Time of Day



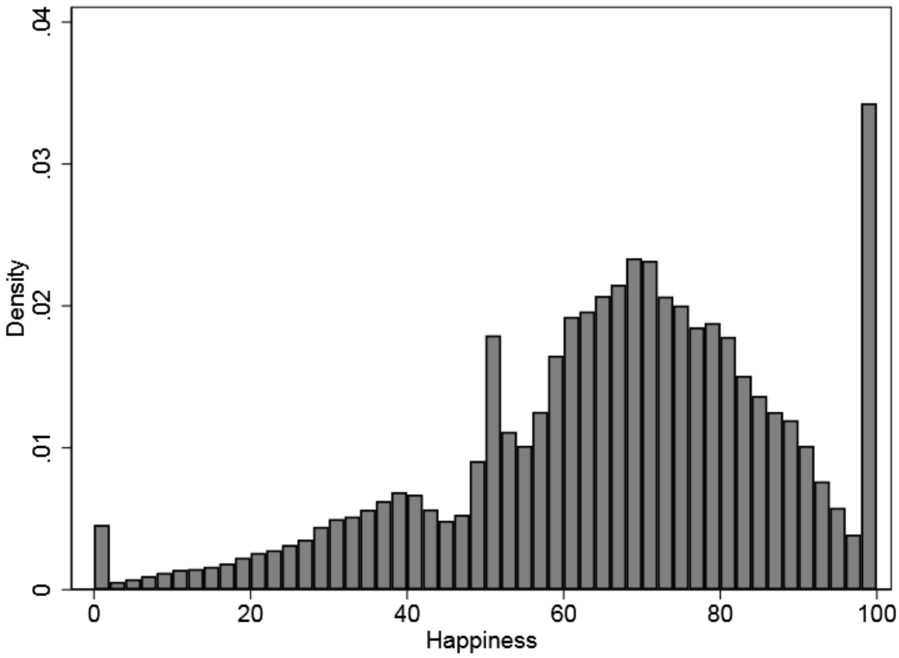
Notes: The figure shows the distribution of responses to our experience-sampling survey in our estimation sample by time of day. Participants were messaged at *random* moments to answer this survey. They could choose between 1, 2, 3, 4, or 5 messages per day and specify daily start and end times to the nearest fifteen minutes (the default being twice a day between 8am and 10pm). Notifications were similar to text messages in terms of sound and vibration.
Sources: Mappiness data, 2010 to 2016, own calculations.

Figure A6: Experience-Sampling Survey – Cumulative Probability of Response by Response Lag (Time Lapsed Between Message and Response



Notes: The figure shows the cumulative probability of responding to our experience-sampling survey by response lag, defined as time elapsed between the random message and response in minutes, in our estimation sample.
Sources: Mappiness data, 2010 to 2016, own calculations.

Figure A7: Experience-Sampling Survey – Distribution of Outcome



Notes: The figure shows the distribution of our outcome – whether an individual feels happy – in our estimation sample. It is obtained from a slider asking: "Do you feel happy?". Answers range continuously (limited only by the pixel resolution of the device) from zero ("Not at all") to 100 ("Extremely"), the initial position being the midpoint.
Sources: Mappiness data, 2010 to 2016, own calculations.

Table A1: Summary Statistics – Intake Survey

	Mean	SD	Minimum	Maximum	N
Age					
... 18 to 24	0.21	0.41	0	1	30,928
... 25 to 34	0.41	0.49	0	1	30,928
... 35 to 44	0.25	0.43	0	1	30,928
... 45 to 54	0.10	0.30	0	1	30,928
... 55 to 64	0.03	0.17	0	1	30,928
... 65 to 74	¡0.00	0.06	0	1	30,928
... 75 or Over	¡0.00	0.02	0	1	30,928
Gender					
... Male	0.51	0.50	0	1	30,928
... Female	0.49	0.50	0	1	30,928
Relationship Status					
... Not in Relationship	0.20	0.40	0	1	30,928
... In Relationship	0.80	0.40	0	1	30,928
Marital Status					
... Never Married	0.60	0.49	0	1	30,928
... Married and Living With Spouse	0.32	0.47	0	1	30,928
... Married but Separated	0.03	0.16	0	1	30,928
... Divorced	0.05	0.21	0	1	30,928
... Widowed	¡0.00	0.06	0	1	30,928
Self-Assessed Health					
... Excellent Health	0.14	0.35	0	1	30,928
... Very Good Health	0.42	0.49	0	1	30,928
... Good Health	0.32	0.47	0	1	30,928
... Fair Health	0.09	0.29	0	1	30,928
... Poor Health	0.02	0.13	0	1	30,928
Employment Status					
... In Full-Time Education	0.12	0.32	0	1	30,928
... Employed or Self-Employed	0.80	0.40	0	1	30,928
... Unemployed and Looking	0.03	0.16	0	1	30,928
... Long-Term Sick or Disabled	0.01	0.10	0	1	30,928
... Looking After Family or Home	0.02	0.15	0	1	30,928
... Retired	0.01	0.09	0	1	30,928
... Other	0.01	0.12	0	1	30,928
Annual Gross Household Income					
... Under £8,000	0.06	0.23	0	1	30,928
... £8,000 to £11,999	0.03	0.17	0	1	30,928
... £12,000 to £15,999	0.04	0.20	0	1	30,928
... £16,000 to £19,999	0.04	0.21	0	1	30,928
... £20,000 to £23,999	0.06	0.23	0	1	30,928
... £24,000 to £31,999	0.11	0.31	0	1	30,928
... £32,000 to £39,999	0.11	0.32	0	1	30,928
... £40,000 to £55,999	0.19	0.39	0	1	30,928
... £56,000 to £71,999	0.14	0.35	0	1	30,928
... £72,000 to £95,999	0.10	0.30	0	1	30,928
... £96,000 or More	0.12	0.32	0	1	30,928
Number of Adults in Household					
... 1	0.20	0.40	0	1	30,928
... 2	0.55	0.50	0	1	30,928
... 3	0.13	0.34	0	1	30,928
... 4 or More	0.12	0.32	0	1	30,928
Number of Children in Household					
... None	0.71	0.45	0	1	30,928
... 1	0.13	0.34	0	1	30,928

Table A1 Continued

	Mean	SD	Minimum	Maximum	N
... 2	0.11	0.32	0	1	30,928
... 3	0.03	0.17	0	1	30,928
... 4 or More	0.01	0.09	0	1	30,928
Region					
... North East	0.03	0.17	0	1	30,928
... North West	0.08	0.27	0	1	30,928
... Yorkshire and the Humber	0.06	0.23	0	1	30,928
... East Midlands	0.05	0.22	0	1	30,928
... West Midlands	0.06	0.23	0	1	30,928
... East of England	0.07	0.26	0	1	30,928
... London	0.24	0.43	0	1	30,928
... South East	0.15	0.35	0	1	30,928
... South West	0.07	0.26	0	1	30,928
... Northern Ireland	0.01	0.11	0	1	30,928
... Scotland	0.06	0.23	0	1	30,928
... Wales	0.03	0.18	0	1	30,928
... Not Reported	0.09	0.28	0	1	30,928

Notes: The table shows summary statistics on individual and household characteristics from our intake survey for our estimation sample. The intake survey was completed only once, prior to and on a different occasion than any collection of data on momentary happiness and activities, so as not to prime respondents. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table A2: Summary Statistics – Experience-Sampling Survey

	Mean	SD	Minimum	Maximum	N
Activities					
Waiting, Queueing	0.02	0.15	0	1	2,234,753
Commuting, Travelling	0.09	0.29	0	1	2,234,753
Working, Studying	0.25	0.43	0	1	2,234,753
In Meeting, Seminar, Class	0.03	0.17	0	1	2,234,753
Cooking, Preparing Food	0.04	0.20	0	1	2,234,753
Housework, Chores, DIY	0.05	0.22	0	1	2,234,753
Shopping, Running Errands	0.03	0.17	0	1	2,234,753
Admin, Finances, Organising	0.04	0.19	0	1	2,234,753
Childcare, Playing With Children	0.04	0.21	0	1	2,234,753
Petcare, Playing With Pets	0.02	0.14	0	1	2,234,753
Care or Help for Adults	0.01	0.07	0	1	2,234,753
Sleeping, Resting, Relaxing	0.10	0.30	0	1	2,234,753
Sick in Bed	0.02	0.12	0	1	2,234,753
Meditating, Religious Activities	¡0.00	0.06	0	1	2,234,753
Washing, Dressing, Grooming	0.04	0.19	0	1	2,234,753
Talking, Chatting, Socialising	0.15	0.36	0	1	2,234,753
Intimacy, Making Love	0.01	0.07	0	1	2,234,753
Eating, Snacking	0.10	0.30	0	1	2,234,753
Drinking Tea or Coffee	0.06	0.25	0	1	2,234,753
Drinking Alcohol	0.05	0.22	0	1	2,234,753
Smoking	0.01	0.11	0	1	2,234,753
Texting, E-Mail, Social Media	0.06	0.23	0	1	2,234,753
Browsing the Internet	0.05	0.22	0	1	2,234,753
Watching TV, Film	0.18	0.38	0	1	2,234,753
Listening to Music	0.06	0.24	0	1	2,234,753
Listening to Speech or Podcast	0.02	0.14	0	1	2,234,753
Reading	0.03	0.18	0	1	2,234,753
Theatre, Dance, Concert	¡0.00	0.06	0	1	2,234,753
Exhibition, Museum, Library	¡0.00	0.05	0	1	2,234,753
Match, Sporting Event	0.01	0.08	0	1	2,234,753
Walking, Hiking	0.01	0.12	0	1	2,234,753
Sports, Running, Exercise	0.01	0.11	0	1	2,234,753
Gardening, Allotment	¡0.00	0.06	0	1	2,234,753
Birdwatching, Nature Watching	¡0.00	0.04	0	1	2,234,753
Computer Games, Smart Phone Games	0.03	0.17	0	1	2,234,753
Hunting, Fishing	¡0.00	0.01	0	1	2,234,753
Other Games, Puzzles	¡0.00	0.06	0	1	2,234,753
Gambling, Betting	¡0.00	0.03	0	1	2,234,753
Hobbies, Arts, Crafts	0.01	0.10	0	1	2,234,753
Singing, Performing	¡0.00	0.06	0	1	2,234,753
Something Else	0.01	0.11	0	1	2,234,753
Other	0.03	0.17	0	1	2,234,753
Companionship					
Spouse, Partner, Girlfriend, or Boyfriend	0.24	0.43	0	1	2,234,753
Children	0.11	0.31	0	1	2,234,753
Other Family Members	0.07	0.26	0	1	2,234,753
Colleagues, Classmates	0.17	0.38	0	1	2,234,753
Clients, Customers	0.02	0.12	0	1	2,234,753
Friends	0.09	0.28	0	1	2,234,753
Other People You Know	0.02	0.12	0	1	2,234,753

Table A2 Continued

	Mean	SD	Minimum	Maximum	N
Alone	0.43	0.50			2,234,753
Place					
At Work	0.24	0.42	0	1	2,234,753
At Home	0.51	0.50	0	1	2,234,753
Elsewhere	0.25	0.44	0	1	2,234,753
Location					
Indoors	0.84	0.36	0	1	2,234,753
Outdoors	0.08	0.28	0	1	2,234,753
In Vehicle	0.07	0.26	0	1	2,234,753

Notes: The table shows summary statistics on activities, companionship, place, and location from our experience-sampling survey for our estimation sample. Participants were messaged at *random* moments and asked to complete the experience-sampling survey. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table A3: Stability of Activity Coefficient – Waiting or Queueing

	Happy (0-100)		
	(1)	(2)	(3)
Waiting, Queueing	-3.31***	-3.11***	-3.61***
	(0.16)	(0.14)	(0.14)
Experience-Sampling Controls (X_{it})			
Other Activities	No	No	Yes
Companionship	No	No	Yes
Place	No	No	Yes
Location	No	No	Yes
Meteorological Conditions	No	No	Yes
Spatial Controls (r)			
Region Fixed Effects	No	Yes	Yes
Temporal Controls (T)			
Holiday-Season Fixed Effects	No	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes
Month Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Number of Individuals	30,928	30,928	30,928
Number of Observations	2,234,753	2,234,753	2,234,753
Adjusted R Squared	0.35	0.38	0.44
Adjusted R Squared Within	0.00	0.02	0.11
F-Test	419.61	81.69	190.45

Robust standard errors clustered two-way at the region and respondent levels in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Individual fixed-effects regression of momentary happiness on activity $k = 1$ (*waiting or queueing*). Column 1 is a parsimonious model without any controls. Column 2 adds spatial and temporal controls, including $8,925$ regional fixed effects at the Middle Layer Super Output Area (MSOA) level and holiday-season, hour-of-day, day-of-week, month, and year fixed effects. Column 3 then adds additional experience-sampling controls, including momentary 42 activities (which can be multiple due to multitasking), 7 types of companionship (which can also be multiple), 3 types of places, 3 types of locations, and current meteorological conditions. See Equation 2 for the model. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table A4: Stability of Income Coefficient

	Happy (0-100)					
	OLS					FE Filtered
	(1)	(2)	(3)	(4)	(5)	(6)
Log Equiv. Annual Gross Household Income	1.39***	1.17***	1.17***	0.91***		0.95***
	(0.35)	(0.19)	(0.19)	(0.19)		(0.09)
Log Annual Gross Household Income					0.91***	
					(0.20)	
Additional Individual-Level Controls (X_i)						
Age	No	No	No	Yes	Yes	Yes
Marital Status	No	No	No	Yes	Yes	Yes
Children	No	No	No	Yes	Yes	Yes
Health	No	No	No	Yes	Yes	Yes
Experience-Sampling Controls (X_{it})						
Activities	No	No	Yes	Yes	Yes	Yes
Companionship	No	No	Yes	Yes	Yes	Yes
Place	No	No	Yes	Yes	Yes	Yes
Location	No	No	Yes	Yes	Yes	Yes
Meteorological Conditions	No	No	Yes	Yes	Yes	Yes
Spatial Controls (r)						
Region Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Temporal Controls (T)						
Holiday-Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Hour-of-Day Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	30,928	30,928	30,928	30,928	30,928	30,928
Number of Observations	2,234,753	2,234,753	2,234,753	2,234,753	2,234,753	2,234,753
Adjusted R Squared	0.00	0.13	0.13	0.21	0.21	-
Adjusted R Squared Within	0.00	0.02	0.02	0.12	0.12	-
F-Test	15.95	62.97	58.50	140.12	140.06	-

Robust standard errors clustered two-way at the region and respondent levels in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Regression of momentary happiness on income. Column 1 is a parsimonious model without any controls. Column 2 adds spatial and temporal controls, including $8,925$ regional fixed effects at the Middle Layer Super Output Area (MSOA) level and holiday-season, hour-of-day, day-of-week, month, and year fixed effects. Column 3 additionally adds experience-sampling controls, including momentary 42 activities (which can be multiple due to multitasking), 7 types of companionship (which can also be multiple), 3 types of places, 3 types of locations, and current meteorological conditions. Column 4 then adds additional time-invariant individual-level controls. Column 5 uses non-equivalised instead of equivalised income. Column 6 uses the filtered fixed-effects approach by Pesharan and Zhou (2016), which estimates individual fixed effects alongside time-invariant controls in a two-step procedure. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table A5: Comparison of Income Coefficients

	Happy (0-100) "Mappiness"			
	Equivalised		Non-Equivalised	
	(1a)	(1b)	(2a)	(2b)
Log Annual Gross Household Income	1.39***	0.91***	1.77***	0.91***
Controls	No	Yes	No	Yes
Number of Individuals	30,928	30,928	30,928	30,928
Number of Observations	2,234,753	2,234,753	2,234,753	2,234,753
	"Track Your Happiness" (Killingsworth, 2021)			
	Restricted Sample		Unrestricted Sample	
	(3a)	(3b)	(4a)	(4b)
Log Annual Gross Household Income	1.13***	0.70***	0.91***	-
Controls	No	Yes	No	Yes
Number of Individuals	41,319	41,319	41,319	-
Number of Observations	2,100,828	2,100,828	2,100,828	-

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: "Mappiness", which forms the basis of the present paper, is an app-based experience-sampling panel study in the UK. Its measure of annual gross household income from all sources is obtained from a categorical variable with twelve categories, whereby the midpoint of each category is used. To equivalise income, it is divided by the square root of the household size. The happiness measure is obtained from a slider that asks "Do you feel happy?", with answers from zero ("Not at all") to 100 ("Extremely"), whereby 50 is the initial position. The models are estimated using ordinary least squares, with controls including age, gender, marital status (including children), and health. "Track Your Happiness", which is described in Killingsworth (2021), is an app-based experience-sampling panel study in the US. Its measure of annual gross household income from all sources is obtained from a categorical variable with fifteen categories (plus additional categories to capture high-income individuals), whereby the midpoint of each category is used. The happiness measure is obtained from a slider that asks "How do you feel right now?", with answers from "Very bad" to "Very good", whereby the initial position is close to "Very bad". The models are estimated using ordinary least squares, with controls including age, gender, marital status, and education level. The restricted sample includes employed, working-age US adults with a minimum annual income of $\$10,000$, the unrestricted sample all respondents.
Source: Mappiness data, 2010 to 2016, own calculations; "Track Your Happiness" data, observation period not reported.

Table A6: Dichotomous-Around-the-Median (DAM) Test (Bloem and Oswald, 2021)

	Happy		
	0-100, Z-Score	1 if $>$ Median, Z-Score	1 if $\geq$ Median, Z-Score
	(1)	(2)	(3)
Waiting, Queueing	-0.22***	-0.14***	-0.14***
	(0.01)	(0.01)	(0.01)
Experience-Sampling Controls (X_{it})			
Other Activities	Yes	Yes	Yes
Companionship	Yes	Yes	Yes
Place	Yes	Yes	Yes
Location	Yes	Yes	Yes
Meteorological Conditions	Yes	Yes	Yes
Spatial Controls (r)			
Region Fixed Effects	Yes	Yes	Yes
Temporal Controls (T)			
Holiday-Season Fixed Effects	Yes	Yes	Yes
Hour-of-Day Fixed Effects	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Number of Individuals	30,928	30,928	30,928
Number of Observations	2,234,753	2,234,753	2,234,753
Adjusted R Squared	0.13	0.38	0.38
Adjusted R Squared Within	0.12	0.07	0.07
F-Test	374.45	146.27	146.54

Robust standard errors clustered two-way at the region and respondent levels in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Individual fixed-effects regression of momentary happiness, standardised to have a mean of zero and a standard deviation of one (i.e. a z-score), on activity $k = 1$ (*waiting or queueing*) (Column 1). We then run the same regression but dichotomise happiness such that it is one for responses above the median (Column 2) or one for responses equal to or above the median (Column 3), and zero otherwise, likewise standardised. All columns control for momentary 42 activities (which can be multiple due to multitasking), 7 types of companionship (which can also be multiple), 3 types of places, 3 types of locations, and current meteorological conditions. We also include spatial and temporal controls, i.e. $8,925$ regional fixed effects at the Middle Layer Super Output Area (MSOA) level and holiday-season, hour-of-day, day-of-week, month, and year fixed effects. See Equation 2 for the model. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016, own calculations.

Table A7: External Validity of Intake Survey – Comparison to UK Household Longitudinal Study ("Understanding Society")

	"Mappiness"		"Understanding Society"			
	Mean	SD	Mean	SD	Normalised Difference	> 0.25?
Age						
... 18 to 24	0.21	0.41	0.11	0.31	0.20	No
... 25 to 34	0.41	0.49	0.16	0.37	0.40	Yes
... 35 to 44	0.25	0.43	0.18	0.38	0.13	No
... 45 to 54	0.10	0.30	0.18	0.39	-0.17	No
... 55 to 64	0.03	0.17	0.16	0.36	-0.32	Yes
... 65 to 74	¡0.00	0.06	0.12	0.32	-0.35	Yes
... 75 or Over	¡0.00	0.02	0.10	0.30	-0.33	Yes
Gender						
... Male	0.51	0.50	0.48	0.50	0.04	No
... Female	0.49	0.50	0.52	0.50	-0.04	No
Relationship Status						
... Not in Relationship	0.20	0.40	N/A	N/A	N/A	N/A
... In Relationship	0.80	0.40	N/A	N/A	N/A	N/A
Marital Status						
... Never Married	0.60	0.49	0.24	0.43	0.56	Yes
... Married and Living With Spouse	0.32	0.47	0.62	0.49	-0.45	Yes
... Married but Separated	0.03	0.16	0.02	0.12	0.06	No
... Divorced	0.05	0.21	0.06	0.24	-0.04	No
... Widowed	¡0.00	0.06	0.07	0.25	-0.24	No
Self-Assessed Health						
... Excellent Health	0.14	0.35	0.16	0.37	-0.05	No
... Very Good Health	0.42	0.49	0.34	0.47	0.13	No
... Good Health	0.32	0.47	0.28	0.45	0.06	No
... Fair Health	0.09	0.29	0.15	0.36	-0.12	No
... Poor Health	0.02	0.13	0.06	0.25	-0.17	No
Employment Status						
... In Full-Time Education	0.12	0.32	0.07	0.25	0.12	No
... Employed or Self-Employed	0.80	0.40	0.55	0.50	0.40	Yes
... Unemployed and Looking	0.03	0.16	0.05	0.23	-0.10	No
... Long-Term Sick or Disabled	0.01	0.10	0.03	0.18	-0.12	No
... Looking After Family or Home	0.02	0.15	0.05	0.22	-0.11	No
... Retired	0.01	0.09	0.23	0.42	-0.52	Yes
... Other	0.01	0.12	0.01	0.09	0.04	No
Annual Gross Household Income						
... Under £8,000	0.06	0.23	0.04	0.18	0.07	No
... £8,000 to £11,999	0.03	0.17	0.06	0.23	-0.10	No
... £12,000 to £15,999	0.04	0.20	0.08	0.27	-0.11	No
... £16,000 to £19,999	0.04	0.21	0.08	0.27	-0.11	No
... £20,000 to £23,999	0.06	0.23	0.07	0.26	-0.05	No
... £24,000 to £31,999	0.11	0.31	0.14	0.35	-0.06	No
... £32,000 to £39,999	0.11	0.32	0.12	0.32	-0.01	No
... £40,000 to £55,999	0.19	0.39	0.18	0.38	0.02	No
... £56,000 to £71,999	0.14	0.35	0.11	0.31	0.07	No
... £72,000 to £95,999	0.10	0.30	0.07	0.26	0.07	No
... £96,000 or More	0.12	0.32	0.06	0.24	0.15	No
Number of Adults in Household						
... 1	0.20	0.40	0.18	0.38	0.04	No
... 2	0.55	0.50	0.52	0.50	0.04	No
... 3	0.13	0.34	0.18	0.38	-0.09	No
... 4 or More	0.12	0.32	0.12	0.33	-0.02	No
Number of Children in Household						

Table A7 Continued

	"Mappiness" Mean	"Mappiness" SD	"Understanding Society" Mean	"Understanding Society" SD	Normalised Difference	> 0.25?
... None	0.71	0.45	0.69	0.46	0.03	No
... 1	0.13	0.34	0.15	0.36	-0.03	No
... 2	0.11	0.32	0.11	0.32	0.00	No
... 3	0.03	0.17	0.03	0.18	-0.01	No
... 4 or More	0.01	0.09	0.01	0.11	-0.03	No
Region						
... North East	0.03	0.17	0.04	0.20	-0.05	No
... North West	0.08	0.27	0.11	0.32	-0.08	No
... Yorkshire and the Humber	0.06	0.23	0.08	0.28	-0.07	No
... East Midlands	0.05	0.22	0.07	0.26	-0.07	No
... West Midlands	0.06	0.23	0.09	0.28	-0.08	No
... East of England	0.07	0.26	0.10	0.29	-0.05	No
... London	0.24	0.43	0.12	0.32	0.23	No
... South East	0.15	0.35	0.14	0.34	0.02	No
... South West	0.07	0.26	0.09	0.28	-0.04	No
... Northern Ireland	0.01	0.11	0.03	0.17	-0.08	No
... Scotland	0.06	0.23	0.08	0.28	-0.08	No
... Wales	0.03	0.18	0.05	0.22	-0.06	No
... Not Reported	0.09	0.28	¡0.00	0.03	0.30	No
Number of Individuals	30,928	-	77,496	-	-	-

Notes: The table compares individual and household characteristics from our intake survey in our estimation sample with those in the nationally representative UK Household Longitudinal Study ("Understanding Society"). To maximise comparability, we restrict Understanding Society to Wave 2 (the years 2010 to 2011, when most respondents selected into our study) and use cross-sectional weights to achieve representativeness. We compare samples in terms of normalised differences, which are scale-free, i.e. independent of sample size. The normalised difference is calculated as $\Delta x = (\bar{x}_t - \bar{x}_c)/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of variable x in the first and second group, respectively. σ^2 denotes the respective variance (Imbens and Rubin, 2015). Imbens and Wooldridge (2009) suggest that a normalised difference greater than 0.25 indicates covariate imbalance. See Section 2 for a description of the data.

Source: Mappiness data, 2010 to 2016; Understanding Society data, 2010 to 2011; own calculations.

Table A8a: External Validity of Experience-Sampling Survey – Comparison to UK Time Use Survey (UKTUS, Week Days)

Weekdays (Monday to Friday)	"Mappiness" Mean	"Mappiness" SD	UKTUS Mean	UKTUS SD	Normalised Difference	> 0.25?
Activities						
Waiting, Queueing	0.02	0.15	N/A	N/A	N/A	N/A
Commuting, Travelling	0.10	0.30	0.09	0.10	0.02	No
Working, Studying	0.33	0.47	0.26	0.30	0.12	No
In Meeting, Seminar, Class	0.04	0.19	0.01	0.06	0.15	No
Cooking, Preparing Food	0.04	0.19	0.06	0.07	-0.10	No
Housework, Chores, DIY	0.04	0.20	0.06	0.09	-0.07	No
Shopping, Running Errands	0.03	0.16	0.04	0.07	-0.10	No
Admin, Finances, Organising	0.04	0.21	¡0.00	0.01	0.21	No
Childcare, Playing With Children	0.04	0.19	0.03	0.09	0.04	No
Petcare, Playing With Pets	0.02	0.13	0.01	0.04	0.02	No
Care or Help for Adults	0.01	0.07	¡0.00	0.02	0.04	No
Sleeping, Resting, Relaxing	0.08	0.26	0.07	0.11	0.01	No
Sick in Bed	0.02	0.12	¡0.00	0.03	0.11	No
Meditating, Religious Activities	¡0.00	0.05	¡0.00	0.02	-0.01	No
Washing, Dressing, Grooming	0.03	0.18	0.04	0.05	-0.05	No
Talking, Chatting, Socialising	0.13	0.33	0.11	0.14	0.04	No
Intimacy, Making Love	¡0.00	0.06	N/A	N/A	N/A	N/A
Eating, Snacking	0.09	0.29	0.10	0.08	-0.05	No
Drinking Tea or Coffee	0.06	0.24	N/A	N/A	N/A	N/A
Drinking Alcohol	0.04	0.20	N/A	N/A	N/A	N/A
Smoking	0.01	0.11	N/A	N/A	N/A	N/A
Texting, E-Mail, Social Media	0.06	0.23	N/A	N/A	N/A	N/A
Browsing the Internet	0.05	0.22	0.04	0.07	0.06	No
Watching TV, Film	0.15	0.36	0.16	0.15	-0.03	No
Listening to Music	0.06	0.24	0.04	0.10	0.07	No
Listening to Speech or Podcast	0.02	0.14	N/A	N/A	N/A	N/A
Reading	0.03	0.17	0.02	0.06	0.03	No
Theatre, Dance, Concert	¡0.00	0.05	¡0.00	0.01	0.03	No
Exhibition, Museum, Library	¡0.00	0.04	¡0.00	0.01	0.02	No
Match, Sporting Event	¡0.00	0.06	¡0.00	0.01	0.05	No
Walking, Hiking	0.01	0.11	0.01	0.02	0.06	No
Sports, Running, Exercise	0.01	0.11	0.01	0.05	-0.01	No
Gardening, Allotment	¡0.00	0.04	0.01	0.04	-0.12	No
Birdwatching, Nature Watching	¡0.00	0.03	¡0.00	0.03	-0.05	No
Computer Games, Smart Phone Games	0.03	0.16	0.01	0.04	0.10	No
Hunting, Fishing	¡0.00	0.01	¡0.00	0.02	-0.02	No
Other Games, Puzzles	¡0.00	0.06	0.01	0.03	-0.06	No
Gambling, Betting	¡0.00	0.02	¡0.00	0.01	-0.01	No
Hobbies, Arts, Crafts	0.01	0.09	0.01	0.03	0.03	No
Singing, Performing	¡0.00	0.06	N/A	N/A	N/A	N/A
Something Else	0.01	0.11	N/A	N/A	N/A	N/A
Other	0.03	0.17	N/A	N/A	N/A	N/A
Companionship						
Spouse, Partner, Girlfriend, or Boyfriend	0.17	0.38	0.22	0.27	-0.10	No
Children	0.08	0.28	0.07	0.20	0.04	No
Other Family Members	0.05	0.23	0.11	0.20	-0.18	No
Colleagues, Classmates	0.23	0.42	0.25	0.27	-0.04	No
Clients, Customers	0.02	0.14	N/A	N/A	N/A	N/A

Table A8a Continued

Weekdays (Monday to Friday)	"Mappiness" Mean	SD	UKTUS Mean	SD	Normalised Difference	> 0.25?
Friends	0.08	0.26	N/A	N/A	N/A	N/A
Other People You Know	0.01	0.12	N/A	N/A	N/A	N/A
Alone	0.45	0.50	0.32	0.28	0.23	No
Place						
At Work	0.32	0.47	0.21	0.28	0.20	No
At Home	0.45	0.50	0.53	0.30	-0.13	No
Elsewhere	0.23	0.42	0.26	0.30	-0.06	No
Location						
Indoors	0.85	0.36	0.81	0.20	0.09	No
Outdoors	0.08	0.27	0.03	0.06	0.16	No
In Vehicle	0.07	0.26	0.08	0.11	-0.01	No
Number of Observations	1,566,474	-	8,288	-	-	-

Notes: The table compares activities from our experience-sampling survey in our estimation sample with those in the nationally representative UK Time Use Survey (UKTUS), on weekdays (Monday to Friday). Note that the UKTUS is available for the years 2014 and 2015 only. We compare samples in terms of normalised differences, which are scale-free, i.e. independent of sample size. The normalised difference is calculated as $\Delta x = (\bar{x}_t - \bar{x}_c)/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of variable x in the first and second group, respectively. σ^2 denotes the respective variance (Imbens and Rubin, 2015). Imbens and Wooldridge (2009) suggest that a normalised difference greater than 0.25 indicates covariate imbalance. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016; UKTUS data, 2014 and 2015; own calculations.

Table A8b: External Validity of Experience-Sampling Survey – Comparison to UK Time Use Survey (UKTUS, Weekends and Holidays)

Weekends (Saturday and Sunday) and Holidays	"Mappiness" Mean	SD	UKTUS Mean	SD	Normalised Difference	> 0.25?
Activities						
Waiting, Queueing	0.02	0.14	N/A	N/A	N/A	N/A
Commuting, Travelling	0.07	0.26	0.08	0.10	-0.02	No
Working, Studying	0.07	0.26	0.09	0.20	-0.05	No
In Meeting, Seminar, Class	¡0.00	0.06	¡0.00	0.03	0.03	No
Cooking, Preparing Food	0.05	0.23	0.06	0.07	-0.04	No
Housework, Chores, DIY	0.07	0.26	0.07	0.09	0.02	No
Shopping, Running Errands	0.04	0.20	0.05	0.08	-0.04	No
Admin, Finances, Organising	0.03	0.16	¡0.00	0.01	0.16	No
Childcare, Playing With Children	0.06	0.24	0.04	0.10	0.10	No
Petcare, Playing With Pets	0.02	0.16	0.02	0.04	0.06	No
Care or Help for Adults	0.01	0.07	¡0.00	0.02	0.05	No
Sleeping, Resting, Relaxing	0.15	0.36	0.11	0.13	0.12	No
Sick in Bed	0.02	0.12	¡0.00	0.03	0.11	No
Meditating, Religious Activities	¡0.00	0.07	0.01	0.03	-0.03	No
Washing, Dressing, Grooming	0.05	0.21	0.05	0.05	-0.04	No
Talking, Chatting, Socialising	0.20	0.40	0.16	0.19	0.08	No
Intimacy, Making Love	0.01	0.10	N/A	N/A	N/A	N/A
Eating, Snacking	0.12	0.32	0.13	0.09	-0.04	No
Drinking Tea or Coffee	0.08	0.27	N/A	N/A	N/A	N/A
Drinking Alcohol	0.07	0.26	N/A	N/A	N/A	N/A
Smoking	0.01	0.12	N/A	N/A	N/A	N/A
Texting, E-Mail, Social Media	0.05	0.22	N/A	N/A	N/A	N/A
Browsing the Internet	0.05	0.23	0.04	0.08	0.06	No
Watching TV, Film	0.24	0.43	0.20	0.17	0.09	No
Listening to Music	0.07	0.25	0.04	0.09	0.09	No
Listening to Speech or Podcast	0.02	0.14	N/A	N/A	N/A	N/A
Reading	0.04	0.20	0.03	0.07	0.05	No
Theatre, Dance, Concert	¡0.00	0.07	¡0.00	0.03	0.02	No
Exhibition, Museum, Library	¡0.00	0.06	¡0.00	0.01	0.05	No
Match, Sporting Event	0.01	0.11	¡0.00	0.03	0.08	No
Walking, Hiking	0.02	0.14	0.01	0.04	0.06	No
Sports, Running, Exercise	0.01	0.12	0.02	0.05	-0.02	No
Gardening, Allotment	0.01	0.08	0.01	0.05	-0.06	No
Birdwatching, Nature Watching	¡0.00	0.05	0.01	0.04	-0.07	No
Computer Games, Smart Phone Games	0.03	0.18	0.01	0.05	0.13	No
Hunting, Fishing	¡0.00	0.02	¡0.00	0.02	-0.02	No
Other Games, Puzzles	0.01	0.08	0.01	0.04	-0.03	No
Gambling, Betting	¡0.00	0.03	¡0.00	0.01	-0.01	No
Hobbies, Arts, Crafts	0.01	0.12	0.01	0.04	0.05	No
Singing, Performing	¡0.00	0.07	N/A	N/A	N/A	N/A
Something Else	0.01	0.12	N/A	N/A	N/A	N/A
Other	0.03	0.18	N/A	N/A	N/A	N/A
Companionship						
Spouse, Partner, Girlfriend, or Boyfriend	0.40	0.49	0.35	0.35	0.08	No
Children	0.16	0.37	0.10	0.25	0.13	No
Other Family Members	0.12	0.33	0.14	0.24	-0.05	No
Colleagues, Classmates	0.02	0.15	0.09	0.19	-0.28	Yes
Clients, Customers	0.01	0.08	N/A	N/A	N/A	N/A

Table A8b Continued

Weekends (Saturday and Sunday) and Holidays	"Mappiness" Mean	SD	UKTUS Mean	SD	Normalised Difference	> 0.25?
Friends	0.12	0.32	N/A	N/A	N/A	N/A
Other People You Know	0.02	0.14	N/A	N/A	N/A	N/A
Alone	0.37	0.48	0.29	0.28	0.15	No
Place						
At Work	0.04	0.19	0.06	0.17	-0.09	No
At Home	0.65	0.48	0.62	0.29	0.04	No
Elsewhere	0.31	0.46	0.31	0.27	-0.00	No
Location						
Indoors	0.84	0.37	0.80	0.21	0.08	No
Outdoors	0.10	0.30	0.04	0.07	0.19	No
In Vehicle	0.06	0.25	0.07	0.09	-0.01	No
Number of Observations	668,279	-	8,245	-	-	-

Notes: The table compares activities from our experience-sampling survey in our estimation sample with those in the nationally representative UK Time Use Survey (UKTUS), on weekends (Saturday and Sunday) and holidays. Note that the UKTUS is available for the years 2014 and 2015 only. We compare samples in terms of normalised differences, which are scale-free, i.e. independent of sample size. The normalised difference is calculated as $\Delta x = (\bar{x}_t - \bar{x}_c)/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of variable x in the first and second group, respectively. σ^2 denotes the respective variance (Imbens and Rubin, 2015). Imbens and Wooldridge (2009) suggest that a normalised difference greater than 0.25 indicates covariate imbalance. See Section 2 for a description of the data.
Source: Mappiness data, 2010 to 2016; UKTUS data, 2014 and 2015; own calculations.

Table A9: Literature Review: VOT by Method

#	Author	Scope	Methodology	Data	VOT	VOT (adj.)
1	DeVany (1974)	Air travel demand	Revealed demand elasticities (based on fares, trip distance, and flight duration)	Observing largest 600 US air travel markets in 1968	7.28 USD/h (1968)	39.51
2	Crafton (1979)	Supermarket purchasing behaviour: Are time savings worth accepting higher prices? Full price = VOT*time + product price	Revealed consumer demand (choice of store, time-to-purchase, and price)	Observing supermarkets (express lanes) and convenience stores customers	12.58 USD/h (1978)	36.44
3	Cauley (1987)	Demand for medical care	Econometric model to impute the VOT from demand elasticity	Medical records from random sample (California long-term medical care patients) + household interviews	7.65 USD/h (1975)	26.85
4	Borisova & Goodman (2003)	Reduction in travel time to repeated mandatory hospital treatment	Stated (contingent valuation): Willingness-to-pay for travel time reduction (WTP); Willingness-to-accept monetary compensation to forego it (WTA)	Patient surveys in Detroit, US in 1999	WTP: 7.32 WTA: 8.65 (wage rate: 9.10) (all USD/h, 1999)	WTP: 8.30 WTA: 9.81 Wage rate: 10.32
5	Portrait et al. (2018)	Children receiving medical care: Three separate units: travel, waiting, and treatment time (parent and patient child)	Stated (contingent valuation)	2013-15 surveys in a large Dutch hospital	Waiting: 11.6, Travel: 4.5, Treatment: 3.0 (all EUR/h, 2014)	Waiting: 10.45, Travel: 4.05, Treatment: 2.70

#	Author	Scope	Methodology	Data	VOT	VOT (adj.)
6	Van den Berg et al. (2017)	Medical patients (non-working, i.e. no wage rate reference; unemployed, retired, long-term sick, etc.) Four separate units: Travel, waiting, admission, treatment time	Stated willingness-to-pay for time reduction (contingent valuation)	2011-13 surveys in Netherlands (N=238)	Travel: 2.21, Waiting: 4.05, Treatment: 3.30 (all EUR/h, 2012)	Travel: 2.08, Waiting: 3.82, Treatment: 3.10
7	Wondemu (2016)	Waiting time in public offices	Stated willingness-to-pay for waiting time reduction (contingent valuation)	2011 surveys in Ethiopia, Nigeria, and South Africa (N=1,193)	2.38 GBP/h (wage rate: 3.40) (2011)	2.76 (wage rate: 3.94)
8	Rotaris et al. (2012)	Travel time amongst university student commuters	Revealed preferences + stated preferences	n/a	Revealed only: 13-18, Both: 1.4-2.8 (all EUR/h, 2012)	Revealed only: 12-17, Both: 1.3-2.6
9	McFadden (1974)	Waiting times in urban transport Units (bus): walking to station, first wait time, travel time, transit time comparison to car (total / travel time only)	Valuation at wage rates	Household surveys in California and traffic data (N=213)	Bus waiting: 2.32, Travel: 1.23, Schedule delay: +3.33, Car traffic congestion: +2.13 (all USD/h, 1974)	Bus waiting: 8.89, Travel: 4.72, Schedule delay: +12.76, Car traffic congestion: +8.16
10	Calfee & Winston (1998)	Urban commuting choices (tolled highway car travel vs. bus); Focus on traffic congestion effects on VOT	Revealed willingness-to-pay + stated WTP	Mail surveys across US metropolitan areas (N=1,170)	3.88 USD/h (1993)	5.07

#	Author	Scope	Methodology	Data	VOT	VOT (adj.)
11	Deacon & Sonstelie (1985)	Motorists' choice of gas stations with longer waiting time but lower gas prices	VOT estimation by occupation, wage income groups	Observations at several California gas stations in 1980 (N=170)	4.46-14.26 USD/h (1980)	10.22-32.69
12	De Vany et al. (1983)	Waiting time in dentist's office	n/a	Survey across dentist practices in US in 1979	8.86 USD/h (1977)	27.62
13	Larson & Shaikh (2007)	Recreational activities (whale watching in California); Framework for VOT estimation that is independent from wage income	Revealed preferences (time and monetary spending for activity)	Surveys at four whale watching sites in US (1991-92, N=1,003)	11.27 USD/h (1992)	15.17

Supplementary Materials

1. Description of App in Apple's App Store
2. Informed Consent Form
3. Surveys

Description of App in Apple's App Store

Mappiness maps happiness across space in the UK. It's part of a research project at the London School of Economics. We'd love to have you on board!

HOW DOES IT WORK?

- You download the app, open it, and sign up
- We beep you once a day to ask how you're feeling, and a few basic things to control for: who you're with, where you are, what you're doing (if you're outdoors, you can also take a photo)
- The data gets sent back – anonymously and securely – to our data store, along with your approximate location from the iPhone's GPS, and a noise-level measure

WHAT'S IN IT FOR YOU?

- Interesting information about your own happiness, which is charted inside the app – including when, where and with whom you're happiest
- The warm glow of helping increase the sum of human knowledge

WHAT'S IN IT FOR US?

- We're particularly interested in how people's happiness is affected by their local environment – air pollution, noise, green spaces, and so on – which the data from Mappiness will be absolutely great for helping investigate
- We hope to have some results published in academic journals, and elsewhere – whatever we produce will be linked from our website: http://mappiness.org.uk

FIND OUT MORE

For more information, visit http://mappiness.org.uk, or download the app, open it, and choose 'Find out more'.

Informed Consent Form

Please read this information carefully.

By tapping "I agree" below, you confirm that:

- The nature and purpose of this research have been explained to your satisfaction.
- You agree to take part in the study.
- You understand that you can withdraw at any time.
- You're at least 18 years old, and this is your iPhone.

Please scroll down to see the rest of the information. You can refer back to it at any time in the 'Info & help' section of the app.

What's this research for? We want to better understand how people's feelings are affected by features of their current environment – things like air pollution, noise, and green spaces.

What will I do? You'll provide some basic demographic and health-related information, and confirm some settings in order to sign up. After that, you'll receive a notification (beep) on this iPhone between one and five times a day, at your choice. This will come at a random moment during hours you agree. The notification will prompt you to open this app, to briefly report how you're feeling and – in very broad terms – who you're with, where you are, and what you're doing. If you're outdoors and you're happy to, you'll take a photo of your surroundings too. (You can also open this app and report on your feelings and situation, unprompted, as often as you like).

How long will it take? The sign-up process should take no more than 5 minutes. The daily reports on your feelings and situation will take about 30 seconds each. You can keep taking part in the study for as long (or short) a period as you want.

What data will I be sharing? While you report your feelings and situation, the app will use your iPhone's GPS (sat-nav) to discover your approximate location. It will also use the microphone to measure ambient noise levels (but it *won't* record any sound). When you finish responding, the app will send the answers, noise level measure, location data and photo (if you took one) to our secure data store.

What will you do with this data? We'll use it solely for our academic research. We'll apply statistical methods to the combined responses from everyone taking part. We'll use the location data to estimate what the environment was like in the places where people responded. And we'll be looking at the effect of this on people's feelings, while controlling for some other potential influences. If you're curious to see what we find, please visit *mappiness.org.uk* from time to time: we'll be posting results there. We also hope to present our findings in academic journals and at conferences, and to make sure policy-makers are aware of anything important. In all cases, we'll never report any individual's responses – only information at the group level.

And the photos? If you take a photo, we may try to classify it, either manually or using a computer program, to add extra information about your immediate surroundings (for example, are there trees visible?). If you explicitly agree – and we'll check this with you for every photo – we may also feature it on a public map at *mappiness.org.uk*.

Is it anonymous? Yes. We won't know who you are. We don't ask for your name or for any other identifying information, and we don't need your phone number to send notifications to your iPhone. In principle, given enough responses, it might be possible to identify you from your location data, but we promise we won't try.

Is it confidential? Yes. We won't disclose your data to any third party unless (1) we're required by law to do so, or (2) we do so under a strict contractual agreement with other academic researchers, exclusively for the purpose of academic research at a recognised institution.

Is it secure? Yes. All communication between this app and our data store is over an SSL-encrypted connection, the same kind used for online banking and shopping. The data store is a firewalled and fully updated Linux server, accessible only over a secure connection.

Is it easy to get out of? Yes! Taking part is completely voluntary. You can withdraw at any time and without giving a reason: just delete this app from your iPhone. You could also ask us to delete all your data from our data store. Alternatively, you can take a break from the study by changing your notifications per day to zero on the Settings screen within the app.

How much data does it use? Not much. Responding to a notification generally uses as much data as sending a brief email (around 1KB). If you're outdoors and take a picture, it's more like viewing a simple web page (15 – 20KB). Getting your status when you open the app uses less than 1KB. Viewing your graphed responses uses about 3KB. So, if you respond to two beeps per day, and you take a photo on 20% of these occasions, you'll use about 350KB per month. (If you have an inclusive data bundle, this is probably less than 0.1% of it.) You may want to turn off data when you're abroad (roaming), though, as this can be very expensive.

I'm not in the UK. Can I take part? You're welcome to, but we may not use your data in our research. And look out for the time difference when setting the hours when you can be beeped: all times in the app are UK times (GMT or GMT+1).

I have another question… If there's anything else you'd like to know, please contact Dr George MacKerron or Dr Susana Mourato:

- Email George at george@mappiness.org.uk. You can do this right now: just tap the button at the top right of this screen.
- Call us on +44 (0)20 3322 4466.
- Or write to us at the Dept. of Geography & Environment, London School of Economics, Houghton Street, London WC2A 2AE.

Thank you!

Surveys

The surveys span multiple screens, delineated below by horizontal rules. Tapping an option suffixed by '>' immediately advances to the next screen. The first screen has a 'Cancel' button that discontinues the questionnaire, and each subsequent screen has a 'Back' button to return to the preceding screen.

Registration survey

Satisfaction

How satisfied are you with your life as a whole nowadays?

Segmented control: (Not at all) 1 / 2 / 3 / 4 / 5 / 6 / 7/ 8 / 9 / 10 (Extremely)

Next >

Health

Is your health in general... ?

Excellent >

Very good >

Good >

Fair >

Poor >

Asthma

Do you suffer from asthma or other respiratory disease?

Yes >

No >

Gender

Are you... ?

Male >

Female >

Birth year

When were you born?

Scrolling picker: 1900 – 2010 (initial position: 1975)

Next >

Marriage

Are you... ?

Never married >

Married and living with spouse >

Married but separated >

Divorced >

Widowed >

Please choose the first that applies, and treat Civil Partnership like marriage

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THIS SCREEN IS NOT SHOWN IF THE PARTICIPANT ANSWERED 'MARRIED AND LIVING WITH SPOUSE' ABOVE

Relationship

And are you currently in a relationship?

Yes >

No >

Work status

Are you... ?

Employed or self-employed >

In full-time education >

Retired >

Unemployed and seeking work >

Long-term sick or disabled >

Looking after family or home >

Other >

Adults

In your household, including yourself, are there. . . ?

1 adult >

2 adults >

3 adults >

4 adults or more >

Please count as adults those aged 16 or above

Children

In your household, are there. . . ?

No children >

1 child >

2 children >

3 children >

4 children or more >

Please count as children those aged 15 or under

Household

Is your gross annual household income from all sources. . . ?

Under £8,000 >

£8,000 – £11,999 >

£12,000 – £15,999 >

£16,000 – £19,999 >

£20,000 – £23,999 >

£24,000 – £31,999 >

£32,000 – £39,999 >

£40,000 – £55,999 >

£56,000 – £71,999 >

£72,000 – £95,999 >

£96,000 or more >

Don't know >

Prefer not to say >

We'd be very grateful if you could answer this question, since it's important to our research

---

Income change

Compared to 3 years ago, is your gross annual household income now. . . ?

Higher than it was >

Just the same >

Lower than it was >

Don't know >

Prefer not to say >

THIS SCREEN IS SHOWN ONLY IF THE PARTICIPANT ANSWERED 'HIGHER THAN IT WAS' ABOVE

Income rise

And finally, compared to 3 years ago, is your gross annual household income now. . . ?

Higher by up to £999 >

Higher by £1,000 – £1,999 >

Higher by £2,000 – £3,999 >

Higher by £4,000 – £7,999 >

Higher by £8,000 – £15,999 >

Higher by £16,000 or more >

Don't know >

Prefer not to say >

THIS SCREEN IS SHOWN ONLY IF THE PARTICIPANT ANSWERED 'LOWER THAN IT WAS' ABOVE

Income fall

And finally, compared to 3 years ago, is your gross annual household income now… ?

Lower by up to £999 >

Lower by £1,000 – £1,999 >

Lower by £2,000 – £3,999 >

Lower by £4,000 – £7,999 >

Lower by £8,000 – £15,999 >

Lower by £16,000 or more >

Don't know >

Prefer not to say >

THE QUESTIONNAIRE DISMISSES ITSELF IMMEDIATELY AFTER THIS SCREEN IS DISPLAYED

Finished

Thank you!

ESM survey

Feelings

Do you feel… ?

Happy
Slider: Not at all … Extremely (initial position: midpoint)

Relaxed
Slider: Not at all … Extremely (initial position: midpoint)

Awake
Slider: Not at all … Extremely (initial position: midpoint)

Next >

People

Please tick all that apply

Are you… ?

Alone, or with strangers only >

Or are you with your… ?

[ ] Spouse, partner, girl/boyfriend

[ ] Children

[ ] Other family members

[ ] Colleagues, classmates

[ ] Clients, customers

[ ] Friends

[ ] Other people you know

Next >

Place

Are you… ?

Indoors >

Outdoors >

In a vehicle >

Place (2)

And are you… ?

At home >

At work >

Elsewhere >

If you're working from home, please choose 'At home'

TAPPING 'ADD OR EDIT NOTES' DISPLAYS A TEXT ENTRY AREA WITH KEYBOARD — THE PARTICIPANT TAPS 'DONE' WHEN FINISHED TO RETURN TO THIS SCREEN

Activities

Please tick all that apply

Just now, what were you doing?

[ ] Working, studying

[ ] In a meeting, seminar, class

[ ] Travelling, commuting

[ ] Cooking, preparing food

[ ] Housework, chores, DIY

[ ] Admin, finances, organising

[ ] Shopping, errands

[ ] Waiting, queueing

[ ] Childcare, playing with children

[ ] Pet care, playing with pets

[ ] Care or help for adults

[ ] Sleeping, resting, relaxing

[ ] Sick in bed

[ ] Meditating, religious activities

[ ] Washing, dressing, grooming

[ ] Intimacy, making love

[ ] Talking, chatting, socialising

[ ] Eating, snacking

[ ] Drinking tea/coffee

[ ] Drinking alcohol

[ ] Smoking

[ ] Texting, email, social media

[ ] Browsing the Internet

[ ] Watching TV, film

[ ] Listening to music

[ ] Listening to speech/podcast

[ ] Reading

[ ] Theatre, dance, concert

[ ] Exhibition, museum, library

[ ] Match, sporting event

[ ] Walking, hiking

[ ] Sports, running, exercise

[ ] Gardening, allotment

[ ] Birdwatching, nature watching

[ ] Hunting, fishing

[ ] Computer games, iPhone games

[ ] Other games, puzzles

[ ] Gambling, betting

[ ] Hobbies, arts, crafts

[ ] Singing, performing

[ ] Something else

Add or edit notes

Next >

BY DEFAULT, THIS DIGITAL CAMERA SCREEN IS SHOWN ONLY WHEN OUTDOORS

Please take a photo straight ahead

Or tap Cancel to skip this step

THIS SCREEN IS SHOWN ONLY IF A PHOTO WAS TAKEN

Map

Add this photo to the public map?

Yes >

No >

THIS SCREEN IS SHOWN ONLY WHEN OUTDOORS AND IN THE RARE EVENT THAT GPS LOCATION ACCURACY IS STILL WORSE THAN 100M. IT ADVANCES AUTOMATICALLY WHEN ACCURACY REACHES 100M OR 60 SECONDS HAS ELAPSED.

Location

Improving location accuracy

Skip >

THE QUESTIONNAIRE DISMISSES ITSELF IMMEDIATELY AFTER THIS SCREEN IS DISPLAYED

Finished

Thank you!

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