Exploring the impact of reporting medium on online crime reporting experiences: comparing live chat with human and AI operators

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Abstract

Driven by societal and technological advancements and the imperative to enhance efficiency, UK police forces have in recent years adopted various technologies to transform their interactions with the public and other criminal justice entities. These initiatives often fall under "transformation" agendas with a significant technological focus, promoting a "channel shift" strategy to facilitate a majority of public interactions through various technologically mediated platforms, such as reporting crimes online using form-based or chat functions. In this study we examine preferences and perceptions in online crime reporting. Participants read a fictitious 'chat' between a victim of crime and a police operator identified as either a human or a chatbot. We find a consistent preference for human operators over chatbots across all scenarios. Participants also responded more positively to the process when (a) the crime involved was less serious and (b) when the outcome was proactive (police attendance) rather than passive (simple recording). Procedural justice emerged as a strong predictor of outcome fairness for both operator types. Human operators were thought to provide clearer explanations, but there were no significant differences in judgements of interpersonal treatment or decision neutrality between human and chatbot operators. Outcome satisfaction was higher when there was a human operator and a proactive outcome. These findings underscore the importance of procedural justice and communication clarity in online crime reporting systems, while also highlighting the complexities of user satisfaction in diverse reporting scenarios.

1. Introduction

In a context of rapid societal and technological change, and intense pressure to operate more efficiently, police organisations in the United Kingdom have in recent years introduced various technologies that change how they interact with other criminal justice actors, internally with colleagues and – crucially – with the public. The introduction of body-worn video, mobile data terminals and the Single Online Home (SOH; an online portal for the public to report issues via a standardised form or Live Chat, get updates and apply for licences among other things), as well as increasing numbers of police social media accounts, mean that police–public 'contact' is increasingly likely to be technologically mediated in some capacity. Many forces are pursuing 'transformation' agendas with a strong technological element for the purposes of efficiency, and the term 'channel shift' is being used within policing to describe efforts to encourage the majority of public contacts to take place using a range of technologically mediated forms.

In a parallel development, many forces have increasingly begun to embrace the concept of procedural justice as a method through which to secure legitimacy and (in turn) public compliance and cooperation. Forces have committed to reform their activities to better reflect a large body of research that underlines the importance of procedural justice in securing legitimacy and (in turn) public compliance and cooperation (e.g., Accenture, n.d; NPCC, n.d.). The most visible example of this trend is His Majesty's Inspectorate of Constabulary

and Fire & Rescue Services (HMICFRS) 'PEEL' inspections (the L stands for legitimacy). In its statutory inspections of the UK's 46 major forces, HMICRS considers the principle of procedural justice to make up a vital aspect of any assessment of the legitimacy of police forces across England and Wales (HMICFRS, 2017).

The extent to which these two trends are compatible has not received sufficient attention, within policing or academia. Legitimacy is central to police operations, in terms of the public's willingness to cooperate and accept the decisions of criminal justice actors (Tyler, 2003, 2006). At the core of procedural justice theory lies the idea that people attend closely to the quality of interactions with authority figures such as police officers, particularly across dimensions of respect, neutrality, transparency and 'voice'. Although it is currently being refined in a number of ways (for example, Bradford et al., 2015 on social identity; Radburn et al., 2018 on group encounters; Nix et al., 2015 on collective efficacy), an unexplored assumption persists within much research on procedural justice in policing contexts: that police–public 'contacts' or 'encounters' are between two humans.

We have argued elsewhere that technological developments in policing that insert technology 'into' interactions between police and policed have been initiated with little regard to how they will be received by the public or what differences in reception there may be between particular 'publics' (Wells et al., 2023). To date very little research has explicitly considered what impact increasing technological mediation will have on public trust and police legitimacy, or indeed how the mediating presence of technology affects how people judge the fairness of their interactions with police. Much of the extant literature on interaction and contact that has heavily influenced policing and policing scholarship appears ill-prepared for what looks to be a fundamental shift in the nature of those interactions. Although technologically mediated contacts may still offer procedural justice, as studies on how social media companies interact with users, for example, have shown (Schoenebeck et al., 2021; Yuan & Lou, 2020), exactly how this plays out in policing contexts remains largely known.

This paper examines the influence of reporting methods on the online crime reporting experience by comparing interactions with live chat police representatives and AI-operated chatbots. Participants are presented with a scenario involving either graffiti on private property or burglary and are guided through the process of reporting these past crimes online. The study investigates how the choice of reporting medium and the type of crime impact individuals' perceptions and judgments about the reporting process. Additionally, the research explores how the reporting outcome, either dispatching an officer promptly (a proactive response) or acknowledging the information without further action (a passive response), affects participants' perceptions and judgments. The study presented here is intended as the first in a series that explore how people might interact with and judge police contacts handled by machines. It is intended to 'clear the ground' by considering what differences there are, if any, between the basic judgements people make about policing interactions handled by machines *vis a vis* humans.

Contacting police online

Reporting crimes and other events online is becoming a prominent practice in UK policing. The Single Online Home (SOH) is the most significant manifestation of the National Police Chiefs Council's (NPCC) Digital Public Contact portfolio, with all 43 'territorial' forces in England and Wales currently being approached to 'onboard' a system designed to provide 'nationally consistent, locally branded services, brought together in a single "digital police

station"' (CDS, n.d.). Without ever encountering a human, wherever a user is in the country, it is intended that they can visit a force website and 'report' (a crime, a traffic incident, a missing person, a fraud or – until recently – a COVID-19 breach), 'tell us about' (possible terrorist activity, a planned event, 'something you've seen or heard' or add information to an existing case), 'apply or register' (for a police vacancy, for a firearms licence, for compensation, or pay a fine for a road traffic offence), 'request' (a collision report, your fingerprints or an Intellectual Property licence) or provide 'feedback' (including 'thanks and complaints' and feedback on the website itself). Running alongside this, individual forces are increasingly using live chats on their websites for reporting crime, including the use of bots for non-emergency matters (HMICFRS, 2020). In some force areas, already, reporting some types of 'minor' crime to the police involves interaction with a chatbot, with a human operator only brought in if it begins to look like a more serious offence actually occurred.

Until only a few years ago, almost all of the interactions listed above would have required a phone call, visit to a police station, or some form or written communication. Telephone or in-person interactions clearly imply direct human-to-human interaction, while in the UK at least written communication with police (instigated by the individual concerned) was relatively rare, not least because the bureaucratic functions fulfilled by many European police organisations have never been part of the police role. For example, the 1988 British Crime Survey found that, overall, 56% of people had contacted the police at least once in the 14 months before interview. Some 9% had called the 999 emergency number, 26% had telephoned a police station, 23% had approached a police officer on the street, and 5% some used other mode such as, presumably, the post (Skogan 1990). While directly comparable up to date figures are not readily available, by 2020 the same survey (now renamed the Crime Survey of England and Wales) reported that only 26% of people had had *any* contact with police in the previous year; some 6% had interacted with police over the phone, 2% at the police station, 2% via social media, 2% via email, 1% had approached officers, and 1% used a police website (ONS, 2022). Many of the other forms of contact reported were clearly police instigated, including 'they knocked at my door' (6%), or related to public meetings and events (5% or more).

Not only has there been a large reduction in levels of contact with police, then, but the nature of that contact has changed. Interactions with police instigated by a member of the public are now much more likely to be over the phone or are, increasingly, virtual. They may not even involve a human police operator. This represents a fundamental shift in the way people can – indeed are expected to – interact with the police.

There are two underlying motivations behind these developments that appear to converge but which, on closer inspection, may sit in some tension. First, from the perspective of many police organisations there is a clear need to manage calls for service more efficiently and effectively. It is known that calls to the 101 non-emergency number often go unanswered, pushing people towards 'inappropriate' use of 999 (HMICFRS 2020). Moreover, despite the figures cited above the *volume* of calls for service received by police has increased significantly in recent years, as has their complexity (ibid.). And while many do not involve 'police matters', the loss of other services often leaves police in the position of being the 'only responder' to, say, a homeless person in crisis. There is therefore a strong push towards managing these calls better, with better triage and automated systems wherever possible (Wells et al., 2023).

Second, however, the NPCC and other police organisations are firmly of the view that "[p]ublic expectations of how they interact with policing are changing. The public now expect us to have

a significant online presence, with a similar level of functionality and ease of use to other services they access on a daily basis" (NPCC, n.d.). Its Digital Public Contact 'portfolio' (or group) aims for victim contact with police "reporting and tracking online" in the belief that this will improve the quality of service offered to victims of crime (ibid). Elsewhere, such efforts are explicitly oriented towards improving public trust (Accenture, n.d.).

Police intentions are therefore directed towards increasing 'standardisation' and 'consistency' of encounters with the public to manage demand, improve the quality of contacts and, in turn, the quality of relationships. Yet, very little research has explicitly considered what impact technological mediation might have on public trust and police legitimacy, nor on the perceptions and experiences of procedural justice we know underpin such judgements. In what follows, we draw on the literature on human/machine interaction as well as existing research on procedural justice in technologically-mediated contexts to inform a study that reflects many of the trends outlined above, and which compares the experience of someone reporting a crime via a chat function with a human operator against a similar function with a Chatbot.

Interacting with machines

In this paper, we assume Chatbots are algorithms, computer agents that apply "rule- based or non-rule based (i.e., machine learning based) approaches to develop an output" (Jussupow et al. 2020: 3). Research on the ways people think about and interact with algorithmic decision-making tools and 'Artificial Intelligence' (AI) – we use these terms interchangeably here – has a complex set of implications in the current context. On the one hand, evidence suggests that algorithmic decision-making is perceived as having less agency and emotional capabilities than humans, and more accurate and rational capabilities (Lee, 2018, Kleinberg, et al. 2018; Longoni et al. 2019). This superior accuracy might be preferable to many people, who may be willing to follow the advice of the data-driven technology over fallible, biased, and misjudged human experience and intuition (McGuire, 2021). Some people who contact the police, that is, may *prefer* to speak to a machine, or at least not mind if they do, particularly if they think it is more likely to be 'right'.

On the other hand, studies have also found that people may see algorithmic decisions as less fair and appropriate than police officer decisions (Hobson et al., 2021). Dietvorst et al. (2015) use the phrase 'algorithmic aversion' to describe a complex set of reactions to AI, which Burton et al. (2018) argue includes: false expectations that affect responses to algorithmic decision-making (for example the idea that error is systematic, 'baked in' and irreparable); concerns about decision control and in general a sense that the decision-maker cannot be considered trustworthy; and an emphasis on the need for human decision-making in contexts marked by uncertainty. While Dietvorst and colleagues (2015, 2018) position aversion as emerging primarily from perceptions or experiences of imperfection (i.e., things going wrong, which seems to evoke a strong response when it is a machine making the error), other research has suggested that aversion can arise before such experiences (Longoni et al. 2019) – the aversion itself can thus be 'baked in' to people's assessments of algorithms.

Jussupow et al. (2020: 4) argue that algorithmic aversion is therefore different to technological resistance, which stems from perceived threats presented by the technology and refers primarily to a preference for the status quo, and also simple rejection, which relates primarily to objective factors such as the quality of the system's suggestions. Both may be important aspects of some people's reactions to AI decision-makers. Studies have shown, for example, that reliability – making the correct decision or offering the correct response – is an

important feature of people's judgement formation, and trust and cooperation can be withdrawn if AI is seen as unreliable (Glikson and Woolley 2020). Yet, algorithmic aversion in a sense goes further, constituting "a subjective evaluation of the algorithm [that] is systematically distorted (Tversky and Kahneman, 1974)", and which can lead to "systematic differences in the way algorithms and human actors are judged". Bellaiche and colleagues (2023), for instance, found that people preferred works of art they thought were produced by a human compared to an AI, *even though they were the same works*, seemingly because they thought the human work more morally authentic.

Perhaps relatedly, there is also evidence that people are more accepting of AI decision-making in routine situations or processes, where the potential costs for the individual is low or easily remedied, than in more complex and/or higher cost scenarios. Lee (2018) found that when the decision-maker (either algorithmic or human) was making a managerial decision about a mechanical task (for example scheduling employee's shift patterns), algorithm and human-made decisions were perceived as equally fair and trustworthy. However, when the decision-maker was considering a human task (e.g., hiring), algorithms were perceived as less fair and trustworthy and evoked more negative emotions than human decisions. Mozafari, Weiger and Hammerschmidt (2021) found that service users trusted 'conversational partners' less if the latter were revealed to be chatbots rather than humans, but only in situations of high 'criticality' – in this case where the interaction had financial implications for the subject.

Nass and Moon (2000: 81) argue that human interactions with digital systems must be considered in their social context. They suggest that people apply "social rules and expectations to computers" (2000, p.81), reading off, as well as displaying, overlearned social behaviours such as politeness and reciprocity, and indeed ascribing personalities to computers. Moreover, implied gender, expertise, politeness and ethnicity all continue to be relevant to the user experience, confirming that social cues and socially learned expectations are relevant even when an interface is technically neutral (Langer, 1992 cited in Nass and Moon, 2000: 90). Moreover, in interactions with a machine embodying an authority figure, Langer suggests "premature cognitive commitment" occurs and "information is accepted uncritically, without attention to other aspects of the situation." (Langer, in ibid, p.90); although, in policing, we might suggest that for some such a commitment could also have the reverse effect (i.e., information is uncritically rejected because it comes from police). In other words, some people are primed to respond to information from police in a positive light, while others are primed to respond in a negative light. Prior experiences of policing may therefore impact on experiences of technologically-mediated policing. Users do not leave all their social learning behind when they find themselves in front of a screen, and they may continue to expect a particular set of things in and from their interaction with 'the police'.

Research on online dispute resolution may also offer some lessons. Here, users are a) engaged in some form of disagreement or conflict; b) the process involves digital, online or computerised elements; and c) a resolution is sought. Rabinovich-Einy and Katsh note that in policing this technology has been viewed as enhancing the convenience or efficiency of proceedings (2014, p.6), but also highlight the potential and risks of introducing digital technologies as a "fourth party"[1]. The introduction of technology is disruptive to a range of

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[1] The other three parties being the defendant, the accuser, and the party being called on to resolve the dispute.

'boundaries' (physical, conceptual, psychological, professional),[2] which, given that the formation of trust and institutional legitimacy is tied to boundaries constructed and shaped through human-to-human interaction, may be disruptive.

Chatbots and procedural justice

Research on procedural justice – an important if not the primary lens through which people view interactions with police agents – adds further nuance. In general, there is good evidence to suggest procedural justice remains important in on-line, virtual and/or automated environments (e.g. Rabinovich-Einy and Katsh 2014; Saulnier and Sivasubramaniam 2021; Tyler et al. 2021). Wider research on what might build trust in AI decision-makers stresses the importance of elements usually considered components of procedural justice, such as transparency, as well as closely associated concepts such as responsiveness (Glikson and Woolley 2020). Yet, while it might be relatively easy for algorithmic decision-makers to demonstrate some aspects of procedural justice, such as neutrality, it may be much harder to them to display others, such as voice (and indeed decision control). More importantly in the current context, we might also assume that the relative weight of procedural justice, and perhaps some of its components, might vary between human compared with algorithmic encounters.

Consider the earliest iterations of procedural justice theory itself (Thibaut and Walker, 1975, Walker et al., 1979). Here, procedural justice was important because it gave those involved in justice processes (e.g., a trial) a sense that they had some measure of input into and therefore control over events. Feeling one has control over, or at least is part of, a decision-making process offers reassurance that the right outcome has been or is likely to be reached, and is generally referred to in the PJT literature as the opportunity to 'voice'. Moreover, much subsequent work has demonstrated that judgements of distributive justice (fairness of outcomes) – and other outcome related measures – are often premised on judgements of procedural justice (fairness of process), not least because people have direct knowledge of the latter and use it to infer the presence of the former, about which it is very hard for them to come to an independent judgement (this has been termed the justice substitutability process; see Lind, 2001 for a review). In a situation where the decision-making process is almost entirely hidden from participants – such as when the interaction is online or the decision is being made by a machine – people may therefore be especially attuned to process fairness because they have little other way of coming to a judgement about its overall quality of the decisions made or the fairness of outcomes reached.

Another important aspect of procedural justice is the ability of the authority involved to explain the reasons for its decisions. The ability to do so, and to demonstrate that decisions have been made in a neutral and unbiased fashion, can be central to people's readiness to accept the decisions authorities make (Tyler, 2003). This may have a number of implications in the current context. If people trust algorithmic decision-makers less, they may be less willing to accept the reasons offered. There may also be a belief that machines are simply less able to explain their decisions, since they lack intentionality and empathy. On the other hand, to the extent that people believe that algorithmic decision-makers are inherently rational, neutral and unbiased,

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[2] albeit in a figurative rather than literal sense. Participation from the public is still necessary, in that they will be needed to report incidents, to act as witnesses, to complete paperwork etc. and if they stop 'turning up' they withdraw their consent.

they may be more ready to believe the decisions they reach are themselves neutral and unbiased.

2. Hypotheses

In this study we explore experimentally the impact of the reporting medium in online crime reporting experiences by comparing live chat with police representatives to chatbot with AI operators. Participants in an on-line study read a realistic 'chat' exchange between a police operative and someone reporting a crime. We manipulate the identity of that operator (human or chatbot), the seriousness of the crime involved (graffiti or burglary), and the immediate outcome offered to the protagonist ('active' police attendance vs 'passive' recording of the crime – we assume the former is more positive or 'better' than the latter). Drawing on the discussion above, four hypotheses guide our analysis.

H1: Given the same 'service', people will judge the human operator more positively than the machine – the idea of algorithmic aversion suggests that all else equal people will prefer a human to be dealing with the issue.

H2: Respondents in the burglary condition will favour the human operator by a greater margin than those in the graffiti condition. When the crime seems more serious there is a stronger preference for human interaction.

H3: Procedural justice will be a stronger predictor of perceptions of outcome fairness in the machine compared with the human conditions. Because AI decision-making processes are more opaque, respondents will rely on fairness judgement to an (even) greater extent when they believe a machine is making the decision.

H4: Respondents will judge decisions made by humans as better explained. Algorithmic aversion indicates there will be a general unwillingness to 'listen' to what is 'said' by a machine.

H5: Respondents will judge decisions made by the machine as more neutral than decisions made by humans, since there is a relatively widespread view that this is a positive aspect of AI decision-making.

H6: Respondents will be more satisfied with the passive outcome in the human conditions: positive outcomes are more important for judging machines positively.

3. Methodology

Participant information

Participants were recruited on Prolific and completed the survey online in August 2023 (pilot) and September 2023 (full study). Only results from the full study are reported here.

In our study, which involved a sample of 640 participants representative of the UK population, gender distribution was nearly equal, with 48% being male (n = 348) and 52% being female (n = 372). Regarding age, 8% of participants fell into the 18-24 age group (n = 60), 22% were aged 25-34 (n = 156), 21% were in the 35-44 age category (n = 150), 16% were aged 45-54 (n = 117), 20% were between 55-64 (n = 142), 12% were aged 65-74 (n =

83), and 2% were 75 years or older (n = 13). In terms of employment status, the majority of participants were employed (63%, n = 455), with 15% being retired (n = 110), 9% self-employed (n = 61), 3% currently studying (n = 20), 3% unable to work (n = 18), 3% out of work or actively seeking employment (n = 24), 3% identified as homemakers (n = 24), and 1% either reported being out of work and not seeking employment (n = 5) or chose 'other' (n = 4). Education levels varied within the sample, with 40% holding a bachelor's degree or its equivalent (n = 290), 15% possessing a master's degree or its equivalent (n = 109), 14% having two or more A-levels or their equivalent (n = 100), 11% holding a diploma or its equivalent (n = 82), 10% having completed five or more GCSEs or their equivalent (n = 75), 5% with 1-4 GCSEs or their equivalent (n = 38), 1% reporting either skills for life (n = 6) or a doctoral degree (n = 9), and 2% selecting 'other' (n = 12). Regarding health, 21% of the participants reported having a long-standing illness, disability, or infirmity (n = 152), while 79% indicated that they did not have any such condition (n = 569).

The majority of participants (81%, n = 584) identified themselves as White, specifically as English, Welsh, Scottish, Northern Irish, or British. A small percentage of participants (4%, n = 32) indicated other White backgrounds, while 2% identified as Asian/Asian British (Indian: n = 13, Chinese: n = 14) or Black/African/Caribbean/Black British (African: n = 13). Additionally, 1% of participants reported their ethnicity as White (Irish: n = 8), Asian/Asian British (Pakistani: n = 9, Bangladeshi: n = 5), Mixed/Multiple ethnic groups (n = 6), Any other Asian background (n = 9), or Black/African/Caribbean/Black British (Caribbean: n = 8). A further 1% of participants chose not to disclose their ethnicity (n = 7). Ethnic groups not explicitly mentioned in this breakdown comprised less than 0.5% of the sample.

Experimental design

We exposed participants to a story involving either the presence of graffiti on private property or a house burglary. Following that, we guided participants through the victim's online reporting experience of the crimes (which had already happened, i.e., these were not crimes in progress). By comparing two reporting channels, one with a live chat police representative and the other with an AI operator (chatbot), we investigated the impact of the reporting medium and crime type on perceptions of and judgements about the process. Furthermore, we explored how the outcome of the reporting process interacted with perceptions of and judgements about the process. The proactive outcome entailed the decision to dispatch an officer to investigate the reported crime 'as soon as possible', while the passive outcome involved acknowledging the provided information without further action.

The study therefore employed a factorial design involving three independent variables: operator type (police representative in live chat or AI-operated chatbot), crime type (graffiti or burglary), and outcome (proactive or passive). This resulted in a total of eight possible experimental scenarios:

1. Police Representative (Live Chat) - Graffiti - Proactive Outcome
2. Police Representative (Live Chat) - Graffiti - Passive Outcome
3. Police Representative (Live Chat) - Burglary - Proactive Outcome
4. Police Representative (Live Chat) - Burglary - Passive Outcome
5. AI (Chatbot) - Graffiti - Proactive Outcome
6. AI (Chatbot) - Graffiti - Passive Outcome
7. AI (Chatbot) - Burglary - Proactive Outcome

8. AI (Chatbot) - Burglary - Passive Outcome

This design allowed for a comprehensive exploration of the impact of operator type, crime type, and reporting outcome on participants' perceptions and judgments during the online crime reporting process, providing valuable insights into user experiences in various reporting scenarios.

The key for Study 1 was to make the conversations essentially identical, while also making it clear that one is a human operator, and one is a machine. The study proceeded as follows.

Procedure

All participants first received an introductory blurb providing information about the study and obtaining their consent to participate. Subsequently, participants were required to input their Prolific ID to ensure eligibility for compensation.

Following this, participants were randomly assigned to one of two narratives: a story featuring unauthorised graffiti on private property or a house burglary. In the graffiti scenario, Jane, returning to her flat after work, encounters the graffiti and opts to report it online, despite her mixed emotions. In the burglary scenario, Jane returns home to find her flat burgled, leading her to report the crime online, overwhelmed by a sense of violation. Detailed vignettes of these scenarios are available in Appendix 1.

Subsequently, participants were again randomly assigned to experience the victim's online reporting process, either through reading a 'live chat' with a police representative or an AI operator (chatbot). In this phase, Jane reports the crime (either graffiti or burglary, depending on the condition they were initially assigned to) to either the police representative or 'Bobbybot'. The reporting process involves providing details, experiencing a 5-minute delay, and concluding the conversation with expressions of gratitude and assurance by either the police representative or Bobbybot, depending on the assigned condition. Transcripts of these chat conversations are available in Appendix 2. The content of these chats, and how they unfolded, was based on observational and interview work conducted in police call handling centres, conducted as part of the larger project of which the current study is just one small part.

Participants were then presented with a series of questions regarding their perceptions of the fairness of the online conversation between Jane and the police or Bobbybot.

Subsequently, the chat between Jane and the police representative/ Bobbybot continued. Here, participants were randomly assigned to observe one of two possible outcomes of the reporting process. The proactive outcome involved dispatching an officer to investigate the reported crime "as soon as possible," while the passive outcome merely acknowledged the information provided without further action. Transcripts of these chat conversations are available in Appendix 3.

Finally, participants responded to a series of questions regarding their perceptions of the fairness of the outcome presented in the conversation they had just read. They were also asked to rate their overall satisfaction with the process, and to answer a series of questions about their views on how the decision reached in the story was communicated to Jane. Finally, participants were asked to provide their demographic information (gender, age,

employment, education, disability, ethnicity), and they were thanked for their participation and debriefed.

Measures[3]

The survey items either related directly to the content of the vignettes or were drawn from existing batteries. Question sets included: Perceptions of the fairness of the interaction process (procedural justice); Perceptions of the fairness of the outcome; Views on how the decision reached in the vignette was communicated to Jane; and Overall satisfaction with the process

Dependent variables

Judgements about process fairness. We used Principal Components Analysis to derive our primary dependent variables. Perceptions of *procedural justice* were measured by a scale derived from nine items probing judgements about the procedural fairness of the police operative's behaviour, including "Thinking about the interaction between Jane and the police, would you agree or disagree that the police:" e.g. "treated Jane with respect and dignitiy", "Were impartial, i.e. acted in a fair and neutral manner", "Listened to Jane before making decisions" (a = .85). All items loaded strongly onto one factor, which was extracted and saved for analysis (mean = 0; SD = 1; min = -2.5; max = 2.7).

Judgements about the outcome. Perceptions of *outcome fairness* were measured by a scale derived from three items (*"Jane got the response from police that she deserved", "Jane received an outcome similar to that others would get in the same situation", "Some types of people receive a better service in these cases than others"*) (a = .82). All items loaded strongly onto one factor, which was extracted and saved for analysis (mean = 0; SD = 1; min = -3.4; max = 1.6). We also include two measures of procedural justice relating to the way the police response or outcome was decided: "*What police were going to do was explained clearly to Jane*" and the police "*Made decisions based on the facts*". Responses were on 5-point agree/disagree scales in each case.

Overall satisfaction with the process. Overall satisfaction was measured by a single item *"If you were Jane, would you have been satisfied with how the police dealt with this case?"*

4. Results

To answer our hypotheses we use regression analysis, primarily for the sake of simplicity.

Judgements about process fairness

Table 1 shows results from two linear regression models predicting perceptions of procedural justice. These provide partial tests of H1 (Given the same 'service', people will judge the human operator more positively than the machine) and H2 (Respondents in the burglary condition will favour the human operator by a greater margin than those in the graffiti condition). Model 1 shows that, holding the crime type constant, participants judged the

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[3] Participants were also presented with questions regarding their reporting preference as well as general questions about their levels of trust in the police, perceptions of police legitimacy, and their future intentions to engage or cooperate with the police; but we do not utilise these measures in the analysis presented.

human operator to be fairer than the chatbot. Holding the operator constant, police behaviour was judged to be fairer in the graffiti case than in the burglary case. Model 2 adds the interaction between operator and crime type, which is not significant in the model. In other words, the 'preference' for the human operator did not vary significantly by crime type.[4]

Table 1: Linear regression models predicting perceptions of process fairness

	Model 1	Model 2
Human (ref: Bot)	0.209**	0.266*
Graffiti (ref: burglary)	0.421***	0.477***
Interaction		
Human x Graffiti		-0.113
Constant	-0.315***	-0.343***
N	640	640

* p<0.05, ** p<0.01, *** p<0.001

Fitted values from Model 1

(95% C.I.)

	Human	Bot
Graffiti	.32 (.18, .45)	.11 (-.03, .24)
Burglary	-.11 (-.24, .03)	-.32 (-.45, -.18)

Fitted values calculated from Model 1 illustrate the magnitude of these effects – notably, the difference between the most favourable condition (human, graffiti) and the least favourable (chatbot, burglary) was quite substantial, .6 of a standard deviation.

Judgements about the outcome

Table 2 turns to judgements about outcome fairness, which provides further evidence in relation to H1 and H2, and also tests H3 (Procedural justice will be a stronger predictor of perceptions of outcome fairness in the machine compared with the human conditions). Model 1 shows that the outcome tended to be judged fairer when there was a human compared with a chatbot operator, when the crime involved was graffiti rather than burglary, and when there was a proactive rather than a passive outcome. Considering potential interaction effects (Models 2 to 4), we found there was not a significant interaction between operator and outcome – the importance of the outcome did not vary by the nature of the operator. Neither did we find an interaction between operator and crime type. However, we did find a significant negative interaction between crime type and outcome – whether the outcome was proactive or passive mattered less when the crime type was graffiti. Finally, Model 5 adds the three-way interaction between operator, crime type and outcome: this is also non-significant.[5]

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[4] A oneway ANOVA, with procedural justice response variable and condition as the factor variable (four categories, operator x crime type) produces the following results: $F_{(3, 636)} = 12.6$, $p<.0005$. 'Raw' group means are almost identical to those presented in Table 1.

[5] A oneway ANOVA, with outcome fairness as the response variable and condition as the factor variable (8 categories, operator x crime type x outcome) produces the following results: $F_{(7, 632)} = 13.3$, $p<.0005$. 'Raw' group means are almost identical to those presented in Table 2.

Table 2: Linear regression models predicting perceptions of outcome fairness

	Model 1	Model 2	Model 3	Model 4	Model 5
Human (ref: Bot)	0.205**	0.208	0.205	0.211**	0.208
Graffiti (ref: burglary)	0.433***	0.433***	0.432***	0.679***	0.672***
Proactive outcome (ref: passive)	0.435***	0.437***	0.435***	0.680***	0.680***
Interactions					
Human x Proactive		-0.005			0.007
Human x Graffiti			0.001		0.013
Graffiti x Proactive				-0.490**	-0.478**
Human x Proactive x Graffiti					-0.024
Constant	-0.538***	-0.539***	-0.538***	-0.652***	-0.651***
N	640	640	640	640	640

* p<0.05, ** p<0.01, *** p<0.001

Fitted values from Model 4
(95% C.I.)

	Human	Bot
Graffiti, Proactive	.43 (.27, .58)	.21 (.06, .37)
Burglary, Proactive	.24 (.07, .41)	.03 (-.14, .19)
Graffiti, Passive	.24 (.07, .41)	-.03 (-.14, .20)
Burglary, Passive	-.44 (-.60, -.28)	-.65 (-.81, -.49)

Fitted values from Model 4 again illustrate the magnitude of these effects. There is a full standard deviation difference in judgements between the most favourable condition (human, graffiti, proactive) to the least favourite (chatbot, burglary, passive). Note also that the human, graffiti, passive outcome is judged as fair as the chatbot, graffiti, proactive outcome.

We also estimated models 'within' each of the four groups formed by the initial operator by crime type manipulation, within which respondents were subsequently randomly assigned to proactive or passive responses. This allows us to hold constant operator and crime type – which affected judgements of procedural justice – while allowing the latter to vary, thus providing a test of H3. The response variable in all models was the measure of outcome fairness described above: the three explanatory variables were outcome, perception of procedural justice and the interaction between the two. Procedural justice was a strong predictor of outcome fairness in all models, but the interaction term was not significant in any.[6] The importance of procedural justice in shaping perceptions of outcome fairness did not seem to vary between the human and chatbot conditions.

Perceptions of decision-making

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[6] For these interactions p>.01 in every case, except the graffiti, chatbot, model where the interaction between procedural justice and outcome was b=.26, p=.052). There is thus some indication that if the operator was a chatbot when the crime was less serious procedural justice was less important if the outcome was proactive, but given the p-value and other results noted caution is needed in interpreting this finding.

Next, we consider respondents views on how the decision reached in the vignette was communicated to Jane (H4 and H5). Table 3 shows results from models predicting first the item, which was concerned with how well the decision was communicated; Table 4 shows results for the second item, which was about whether the decision was made based on the facts. As above, we find that respondents were more likely to judge the clarity of explanation positively, and that the decision was made based on the facts, in the graffiti (compared with the burglary) and the proactive (compared with the passive) outcome conditions. Yet, while they were also significantly more likely to judge that the human had been clearer than the chatbot (see Table 3), the difference between the human and chatbot conditions when it came to the decision being made based on the facts was smaller, and non-significant at the conventional 5% level (see Table 4). While this finding needs to treated with some caution – note the relatively large effect seizes in Table 4, and the p value are less than .1 – there is therefore some evidence to suggest that while respondents tended to think that the human operator gave a better explanation, they were not more likely to think the AI operator made more fact-based decisions.

Table 3: Ordinal logistic regression models predicting clarity of explanation

	Model 1	Model 2	Model 3	Model 4	Model 5
Human (ref: Bot)	0.508***	0.503*	0.564**	0.508***	0.667*
Graffiti (ref: burglary)	0.454**	0.454**	0.512*	0.547**	0.749*
Proactive outcome (ref: passive)	0.966***	0.960***	0.966***	1.055***	1.166***
Interactions					
Human x Proactive		0.011			-0.227
Human x Graffiti			-0.117		-0.394
Graffiti x Proactive				-0.187	-0.459
Human x Proactive x Graffiti					0.54
N	640	640	640	640	640

* p<0.05, ** p<0.01, *** p<0.001

Table 4: Ordinal logistic regression models predicting views on whether the decision was made based on the facts

	Model 1	Model 2	Model 3	Model 4	Model 5
Human (ref: Bot)	0.278+	0.359+	0.374+	0.292*	0.499+
Graffiti (ref: burglary)	0.349*	0.352*	0.443*	0.701***	0.848**
Proactive outcome (ref: passive)	0.682***	0.763***	0.685***	1.042***	1.169***
Interactions					
Human x Proactive		-0.163			-0.252
Human x Graffiti			-0.19		-0.293
Graffiti x Proactive				-0.709*	-0.824+
Human x Proactive x Graffiti					0.233
N	640	640	640	640	640

+ p<.1, * p<.05, ** p<.01, *** p<.001

Overall satisfaction with the process

Finally, we turn to overall satisfaction with the process – or, at least, how satisfied respondents thought Jane would have been. We use ordinal logistic regression to model responses to the five-category response variable to test H6 (Respondents will be more satisfied with the passive outcome in the human conditions). Table 5 shows the results, which are strikingly similar to those presented above. Model 1 in Table 5 shows that overall satisfaction tended to be higher when there was a human compared with a chatbot operator, when the crime involved was graffiti rather than burglary, and when there was a proactive rather than a passive outcome. The interaction between operator type and outcome was non-significant (Model 2), implying that outcome was equally important for overall satisfaction in the human and chatbot conditions. We also find, again, that the outcome was more important in the burglary compared to the graffiti conditions (Model 4).

Table 5: Ordinal logistic regression models predicting outcome satisfaction

	Model 1	Model 2	Model 3	Model 4	Model 5
Human (ref: Bot)	0.389**	0.401*	0.141	0.393**	0.167
Graffiti (ref: burglary)	1.219***	1.219***	0.967***	1.548***	1.280***
Proactive outcome (ref: passive)	1.392***	1.404***	1.394***	1.721***	1.750***
Interactions					
Human x Proactive		-0.024			-0.04
Human x Graffiti			0.517		0.551
Graffiti x Proactive				-0.673*	-0.651
Human x Proactive x Graffiti					-0.048
N	640	640	640	640	640

* p<0.05, ** p<0.01, *** p<0.001

5. Discussion

Six hypotheses were tested in this study. Respondents generally favoured human operators over chatbots, indicating a preference for human interaction in the online crime reporting process (H1). While human operators were preferred overall, there was no significant difference in preference for human operators between different crime types, suggesting that this preference held regardless of the type of crime reported (H2). Procedural justice was identified as a strong predictor of outcome fairness in both human and chatbot-operated conditions, highlighting the importance of transparent and just reporting procedures (H3). Respondents perceived human operators as offering clearer explanations compared to chatbot operators (H4). The study did not find a significant difference in judgments of the neutrality of decisions made by humans vs. chatbots (H5). The data does not indicate that positive outcomes are more important for machine-operators: participants were not more satisfied with the passive outcome in the human conditions. Overall satisfaction was influenced by various factors including the type of operator and type of crime, but not by the interaction between operator type and outcome (H6).

Our finding that participants generally favoured human operators over chatbots in online crime reporting aligns with the concept of algorithmic aversion (Dietvorst et al., 2015), where people exhibit a preference for human decision-making due to concerns about trustworthiness

and a perceived need for human involvement in uncertain situations. While some studies have suggested that algorithmic policing decisions may be viewed as more or less fair depending on context (Hobson et al., 2021), our results identify what seems to be a prevalent preference for human interaction in this specific context. This in turn seems to align with the idea that algorithmic aversion can exist even before encountering errors in AI systems (Longoni et al., 2019). The concept of algorithmic aversion also indicates that there will be a general unwillingness to 'listen' to what is 'said' by a machine (Jussupow et al., 2020; Glikson and Woolley 2020), which is in line with our finding that respondents perceived human operators as offering clearer explanations compared to chatbot operators – even though, of course, the same explanation was offered in each case.

By contrast, our finding that there was no significant difference in the strength of preferences for human operators across different crime types contradicts the notion that people prefer human interaction when the situation involved is more serious or consequential (Lee, 2018; Mozafari, Weiger & Hammerschmidt, 2021). Moreover, our results did not support the hypothesis that respondents would be more satisfied with passive outcomes in the human conditions; or, to put it another way, that people are more outcome-oriented when they are dealing with machines.

Similarly, the finding that procedural justice was as strong a predictor of outcome fairness in both human and chatbot-operated conditions challenges the hypothesis that AI decision-making processes, being more opaque, would lead respondents to rely more heavily on fairness judgments when they believe a machine is making the decision. That said, it is also the case that procedural justice was no *less* important in the AI conditions, either. The overall conclusion from many of our findings here seems to be that people do care about, and identify, procedural justice (or injustice) in interactions with machines – it's just that they tend to judge the behaviour of entities they believe to be human as more procedurally fair than identical behaviour on the part of entities they believe to be machines. In effect, the latter start from a lower base.

It is also worth considering some of our other findings. As well as the consistent preference to human operators, participants also judged the graffiti reporting process more favourably than the burglary process, and the proactive outcome as better than the passive, although this effect was largely confined to the burglary conditions. The latter finding is perhaps not surprising – i.e., people value an active police response to crime events, particularly when these are more serious – but the former suggests that on-line reporting of the type considered here should be confined to less serious crimes. Which is indeed the current position across all forces we are aware of; greater moves towards automation might not, on this evidence, be well received by those who need to use such systems.

Practical implications

In addition to the point above our findings have several other practical implications for online crime reporting for policing.

Preference for Human Operators. Since respondents tended to judge human operators more positively than chatbot operators, police departments should consider the continued importance of incorporating human interaction or assistance in their online crime reporting systems, providing access to human operators wherever possible.

Impact of Crime Type. While there may not be a significant difference in the strength of the preference for human operators between different crime types, our results indicate that crime type can influence people's perceptions of procedural justice. While the reporting processes involved were inevitably not perfectly identical, the extent of the difference in perceptions of procedural justice between the graffiti and burglary conditions is striking (see Table 2 above). More work is needed to explore why this the case. It may be, for example, that people have higher expectations of procedural justice when the crime is more serious. There may be a need, therefore, for police to tailor their online reporting systems and responses to account for these varying expectations.

Procedural Justice in on-line interactions. The study shows that procedural justice is a strong predictor of perceptions of outcome fairness and overall satisfaction in both human and chatbot conditions. Therefore, ensuring that online reporting systems are designed to provide transparent, fair, and procedurally just interactions is critical. Clear and respectful communication, adherence to established procedures, and fair treatment are essential components. We also find that respondents perceived human operators as providing clearer explanations than chatbot operators. If they are considering automated reporting systems police departments should therefore focus on enhancing the clarity and comprehensibility of responses.

Outcome Satisfaction. Our findings indicated that satisfaction with the outcome reached was influenced by various factors, including the type of operator and type of crime. Police departments should take a holistic approach to manging the outcomes – or at least outputs – of their online reporting processes. Proactive responses, when possible, may lead to higher satisfaction. However, it's also essential to manage expectations and communicate effectively when outcomes are passive. Our results indicate that people attend to both process *and* outcome.

Limitations and future directions

While this study has provided valuable insights into the impact of reporting methods on the online crime reporting experience, several limitations should be acknowledged, along with suggestions for future directions. Firstly, the study relied on hypothetical scenarios and vignettes to simulate reporting experiences. Although this approach allowed for controlled conditions, it may not fully capture the complexities, emotions, and nuances of real-life crime reporting situations. Future research should aim to complement this approach with the analysis of real-world data or qualitative interviews with actual crime victims and witnesses to provide a more comprehensive understanding of the phenomena under investigation. Secondly, the study focused on only two crime types, namely graffiti and burglary. Expanding the range of crime types considered would be beneficial in order to ascertain whether the findings generalise across different offence categories. Furthermore, variations in crime severity and characteristics may influence reporting behaviours and perceptions differently. Thirdly, the study's findings may be sensitive to the context in which it was conducted. The cultural, regional, and jurisdictional context can play a significant role in shaping individuals' perceptions and behaviours in reporting crimes. Thus, future research should investigate whether the results hold true across diverse locations and populations to ensure broader generalisability. Lastly, because the study primarily relied on participants' responses to hypothetical scenarios, responses may not fully reflect individuals' actual behaviours in real reporting situations, where emotions, urgency, and other contextual factors

come into play. To address this limitation, future research could employ mixed-methods approaches that combine survey responses with observational data or interviews.

6. Conclusion

This study tested six hypotheses regarding online crime reporting preferences. It found that respondents generally preferred human operators over chatbots for reporting crimes, regardless of the type of crime (H1 and H2). Procedural justice was identified as a key factor affecting outcome fairness in both human and chatbot-operated conditions (H3), and respondents perceived human operators as providing clearer explanations compared to chatbot operators (H4). However, there was no significant difference in the neutrality of decisions made by humans and chatbots (H5), and outcome satisfaction varied depending on factors such as the type of operator and the type of crime reported, with proactive outcomes leading to higher satisfaction (H6).

Collectively, our findings emphasise the importance of a user-centred approach when developing and implementing online crime reporting systems. Ensuring procedural justice, clear communication, and human interaction when needed can lead to higher user satisfaction and trust in the online reporting process. Police departments should continuously monitor and improve their online reporting systems based on user feedback to enhance public engagement and cooperation in reporting and preventing crime. Although this study has provided valuable insights, there are certain limitations that need to be addressed for a more comprehensive understanding of online crime reporting dynamics. These limitations include the use of hypothetical scenarios, a narrow focus on specific crime types, potential context-specific findings, and reliance on participant responses to hypothetical situations. To enhance our understanding, future research should consider incorporating real-world data and qualitative interviews, broadening the scope of crime types studied, exploring cross-cultural variations, and adopting mixed-methods approaches to better address the contextual and behavioural aspects of online crime reporting. Such efforts can ultimately lead to improved online reporting systems and enhanced public engagement with police.

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Appendix 1. Condition 1: crime type (graffiti or burglary)

Graffiti

Please read the story below carefully. You will next be asked a few questions about this story.

Jane had a long day at work and was looking forward to going back to her flat in a quiet part of Birmingham to relax. As she walked down the street towards her building, she noticed some graffiti on the wall of her own building. The graffiti was colourful and intricate, but it was clearly done without permission. Jane paused to take a closer look at the graffiti. As she examined it, she felt a mix of emotions. On the one hand, she admired the skill and creativity of the artist who created it. On the other hand, she felt a sense of frustration that someone would deface her property in this way. Jane felt that she had to report the graffiti to the authorities, but the thought of going through the process of reporting it made her anxious and overwhelmed.

Jane checked the website of her local police force, which suggested that the easiest and quickest way to report the crime was online via the force website. The website directed her to an online reporting portal. She followed the instructions to report the crime online.

Please click on the button to Proceed.

Burglary

Please read the story below carefully. You will next be asked a few questions about this story.

Jane lives alone in a small flat in a quiet part of Birmingham. One day, when she returned home from work, she found that her front door was ajar. As she stepped inside, she noticed that her belongings had been rifled through and some of her most treasured possessions were missing. She felt violated and unsafe in her own home. As she looked around, she noticed that the window had been forced open, confirming her suspicion that she had been burgled. Jane knew that she had to report the crime to the police, but the thought of going through the process of reporting it made her anxious and overwhelmed.

Jane checked the website of her local police force, which suggested that the easiest and quickest way to report the crime was online via the force website. The website directed her to an online reporting portal. She followed the instructions to report the crime online.

Please click on the button to Proceed.

Appendix 2. Condition 2: operator type (police representative in live chat or AI-operated chatbot)

Police representative graffiti

Jane logged onto the portal, and after she had entered some basic details about herself, she realised that she would be communicating with the police via a live-chat function while she went through the reporting process.

Specifically, that she would be communicating with **a police representative**, i.e. a human live chat operator.

Please take the time to read the online conversation between Jane and **a police representative** by clicking on the button below.

Police Representative: Hi Jane. My name is Robin. How can I assist you today?

Jane: Hi, I wanted to report some graffiti that I spotted on the side of my building earlier today.

Police Representative: OK. First, can I confirm your address?

Jane: It's 15c The High Street.

Police Representative: Thank you. Could you describe what happened? Please provide the details of the graffiti, such as its location and the graffiti itself.

Jane: The graffiti is on the side of the wall of my block of flats. It's quite large, covering most of the wall. As for the graffiti itself, it's very colourful and really quite interesting, but there are no words or messages that I can see.

Police Representative: Thank you for the information. We'll add it to our records. Do you have any other details to share?

Jane: I don't understand what you mean – like what?

[5-minute delay]

Jane: Hello? Are you still there?

Police Representative: I'll be right with you.

Police Representative: Do you have any additional information you would like to share about the graffiti?

Jane: No, I already gave you everything.

Police Representative: Understood, thank you. We'll do our best to resolve the issue. Please

contact us if you have additional information or questions.

Jane: Thank you.

Police Representative: You're welcome. We're here to help.

AI Chatbot graffiti

Jane logged onto the portal, and after she had entered some basic details about herself, she realised that she would be communicating with the police via a live-chat function while she went through the reporting process.

Specifically, that she would be communicating with **an AI chatbot**, i.e. a computer program that utilises artificial intelligence techniques to stimulate human-like conversation and interact with users through text-based communication.

Please take the time to read the online conversation between Jane and **an AI chatbot** by clicking on the button below.

BobbyBot: Hi Jane. I am BobbyBot. How can I assist you today?

Jane: Hi, I wanted to report some graffiti that I spotted on the side of my building earlier today.

BobbyBot: OK. First, can I confirm your address?

Jane: It's 15c The High Street.

BobbyBot: Thank you. Could you describe what happened? Please provide the details of the graffiti, such as its location and the graffiti itself.

Jane: The graffiti is on the side of the wall of my block of flats. It's quite large, covering most of the wall. As for the graffiti itself, it's very colourful and really quite interesting, but there are no words or messages that I can see.

BobbyBot: Thank you for the information. We'll add it to our records. Do you have any other details to share?

Jane: I don't understand what you mean – like what?

[5-minute delay]

Jane: Hello? Are you still there?

BobbyBot: I'll be right with you.

BobbyBot: Do you have any additional information you would like to share about the graffiti?

Jane: No, I already gave you everything.

BobbyBot: Understood, thank you. We'll do our best to resolve the issue. Please contact us if you have additional information or questions.

Jane: Thank you.

BobbyBot: You're welcome. We're here to help.

Police representative burglary

Jane logged onto the portal, and after she had entered some basic details about herself, she realised that she would be communicating with the police via a live-chat function while she went through the reporting process.

Specifically, that she would be communicating with **a police representative**, i.e. a human live chat operator.

Please take the time to read the online conversation between Jane and **a police representative** by clicking on the button below.

Police Representative: Hi Jane. My name is Robin. How can I assist you today?

Jane: Hi, my house was burgled while I was at work.

Police Representative: OK. First, can I confirm your address?

Jane: It's 15c The High Street

Police Representative: Thank you. Please describe what happened. Provide as much detail as you can – for example, do you know when or how the burglary occurred?

Jane: It happened today between 9am and 5pm. They broke the back window to get in. It looks they've been in the lounge and my bedroom. They took my TV, laptop, and some jewelry. Everything is a real mess. I'm really upset and scared. I feel violated.

Police Representative: Thank you for the information. We'll add it to our records. Do you have any other details to share? Jane: I don't understand what you mean – like what?

[5-minute delay]

Jane: Hello? Are you still there?

Police Representative: I'll be right with you.

Police Representative: Do you have any additional information you would like to share about the burglary?

Jane: No, I already gave you everything.

Police Representative: Understood, thank you. This will be reviewed and may be passed onto the investigations team. Please contact us if you have additional information or questions.

Jane: Thank you.

Police Representative: You're welcome. We're here to help.

AI Chatbot burglary

Jane logged onto the portal, and after she had entered some basic details about herself, she realised that she would be communicating with the police via a live-chat function while she went through the reporting process.

Specifically, that she would be communicating with **an AI chatbot**, i.e. a computer program that utilises artificial intelligence techniques to stimulate human-like conversation and interact with users through text-based communication.

Please take the time to read the online conversation between Jane and **an AI chatbot** by clicking on the button below.

Bobby Bot: Hi Jane. I am BobbyBot. How can I assist you today?

Jane: Hi, my house was burgled while I was at work.

Bobby Bot: OK. First, can I confirm your address?

Jane: It's 15c The High Street

Bobby Bot: Thank you. Please describe what happened. Provide as much detail as you can – for example, do you know when or how the burglary occurred?

Jane: It happened today between 9am and 5pm. They broke the back window to get in. It looks they've been in the lounge and my bedroom. They took my TV, laptop, and some jewelry. Everything is a real mess. I'm really upset and scared. I feel violated.

Bobby Bot: Thank you for the information. We'll add it to our records. Do you have any other details to share? Jane: I don't understand what you mean – like what?

[5-minute delay]

Jane: Hello? Are you still there?

Bobby Bot: I'll be right with you.

Bobby Bot: Do you have any additional information you would like to share about the burglary?

Jane: No, I already gave you everything.

Bobby Bot: Understood, thank you. This will be reviewed and may be passed onto the investigations team. Please contact us if you have additional information or questions.

Jane: Thank you.

Bobby Bot: You're welcome. We're here to help.

Appendix 3. Condition 3: outcome (proactive or passive)

Now, returning to Jane's chat with Robin...

Please take the time to read the online conversation between Jane and **the police representative** below.

Police Representative: Thank you for reporting this crime. We take it very seriously. There have been a number of incidents like this in your area recently, so we will dispatch police officers to your property. Is there anything else you would like to add?

Jane: No, that's it. Thank you for your help.

Police Representative: You're welcome. We'll keep you updated on the investigation.

Police Representative: If you need to update us about this case please contact us via live-chat or 101. If you are in immediate danger or the crime is in-progress call 999.

Now, returning to Jane's chat with Robin...

Please take the time to read the online conversation between Jane and **the police representative** below.

Police Representative: Thank you for reporting this crime. There have been a number of incidents like this in your area recently, so we have taken note of your report, and will action it as soon as we can. We cannot give you an exact date or time for this action at present. Is there anything else you would like to add?

Jane: No, that's it. Thank you.

Police Representative: You're welcome. Have a good day.

Police Representative: If you need to update us about this case please contact us via live-chat or 101. If you are in immediate danger or the crime is in-progress call 999.

Now, returning to Jane's chat with BobbyBot...

Please take the time to read the online conversation between Jane and **the AI Chatbot** below.

Bobby Bot: Thank you for reporting this crime. We take it very seriously. There have been a number of incidents like this in your area recently, so we will dispatch police officers to your property. Is there anything else you would like to add?

Jane: No, that's it. Thank you for your help.

Bobby Bot: You're welcome. We'll keep you updated on the investigation.

Bobby Bot: If you need to update us about this case please contact us via live-chat or 101. If you are in immediate danger or the crime is in-progress call 999.

AI Chatbot Passive outcome

Now, returning to Jane's chat with BobbyBot...

Please take the time to read the online conversation between Jane and **the AI Chatbot** below.

Bobby Bot: Thank you for reporting this crime. There have been a number of incidents like this in your area recently, so we have taken note of your report, and will action it as soon as we can. We cannot give you an exact date or time for this action at present. Is there anything else you would like to add?
Jane: No, that's it. Thank you.

Bobby Bot: You're welcome. Have a good day.

Bobby Bot: If you need to update us about this case please contact us via live-chat or 101. If you are in immediate danger or the crime is in-progress call 999.