Predicting Police Integrity: An Application of Support Vector Machines (SVM) to the Police Integrity Instrument

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Abstract
Research using the 11-scenario police integrity instrument designed by Klockars et al. document a range of factors influencing the willingness to report a fellow officer for police crime and police misconduct. A consistent quandary within this scholarship is that while some findings are consistent, when disaggregated by scenario type, there are wide variations obscuring patterns that may allow for targeted interventions improving police integrity. This study applies support vector machines (SVMs) to construct predictors for 608 responses to the Police Integrity Instrument from police officers enrolled in a police university for in-service training in China. Results confirm that while perceptions of seriousness remain the most successful predictors of the self-reported willingness to report a fellow officer, perceptions of seriousness associated with ethical dilemmas display high survivability suggesting targeted interventions may be an effective pathway towards improving police integrity.

Keywords Police Integrity Instrument · Support vector machines · Police Misconduct · Police Crime · Code of Silence

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Introduction

Decades of research associated with police misconduct suggest a complex system of informal rules governing the willingness to report a fellow officer (Skolnick, 2005; Klockars et al., 2000; Skolnick & Fyfe, 1993). This code of silence insulates those who perpetrate misconduct by inhibiting fellow officers from reporting behavior—even when the charges against an officer are deemed egregious (Caldero & Crank, 2011; Crank, 2004; Westley, 1970). Efforts to understand the relationship, or lack thereof, between the seriousness of the offense and the willingness to report show a powerful influence between increasing perceptions of seriousness among officers to increase the likelihood that an officer would report a fellow officer (Ivković & Sauerman, 2016; Kutnjak Ivković & Kang, 2012; Ivković et al., 2016b; Wu et al., 2018; Wu & Makin, 2019). However, a persistent quandary within the body of research associated with police integrity is that while some findings are consistent when disaggregated by scenario type, there are wide variations in the factors contributing to perceptions of seriousness and the willingness to report (see Kutnjak Ivković et al., 2022; Wu & Makin, 2019). This is particularly important given the increasing research on police integrity, ongoing reform efforts to improve ethical thinking behavior, and combating the blue wall of silence (Skolnick, 2005). Of the many challenges facing reformers, one often highlighted is that while you can educate and train officers on the seriousness of given examples of behavior that is inconsistent with police integrity, there are latent factors contributing to the unwillingness to report. Despite efforts to increase beliefs of seriousness, some may deem the behavior serious, though they are unwilling to report a fellow officer. As such, reformers may tailor efforts through targeted interventions. However, reformers remain relatively uninformed about who to target for such interventions and how best to deliver the intervention (Greene, 2014).

Recognizing that police integrity displays a range of contours, understanding these contours may benefit from an alternative analytical approach. One particularly unique feature of the police integrity instrument is the range of scenarios (Klockars et al., 2000). As researchers have revealed, those scenarios display considerable variability in how they are ranked by seriousness and willingness to report (Klockars et al., 2004). Leveraging the variability within how officers respond to the integrity scale and a robust data set associated with individual, organizational, and environmental factors, this research introduces an alternative analytical approach to extricating relationships within the data. As such, this research employs support vector machines (SVMs) to understand the underlying patterns within these data, which can inform to what extent tailoring is warranted and, if warranted, how to target training and education programs that maximize increasing the willingness to report, therefore decreasing the "code of silence." Modeling the willingness to report is inherently complex because ethical decision-making does not exist in an isolated setting. Individual, organizational, and environmental factors demonstrate direct and indirect effects, which are highly dimensional and can be non-linear. SVM is more robust to outliers, which in our cases are those reporting on each end of the spectrum (serious or not serious | report or not report), models non-linear relationships more effectively (Fig. 1), and minimizes overfitting (Schölkopf et al., 1999). The application of SVM allows us to visualize the relative influence of each predictor on the willingness to report, revealing this level of complexity supporting the "grey" area and, thus, where interventions can be tailored based on these factors.

China is an ideal research site to explore the multi-dimensional dynamics of the code of silence, given the observed strong code of silence in China's policing (see Wu & Makin,

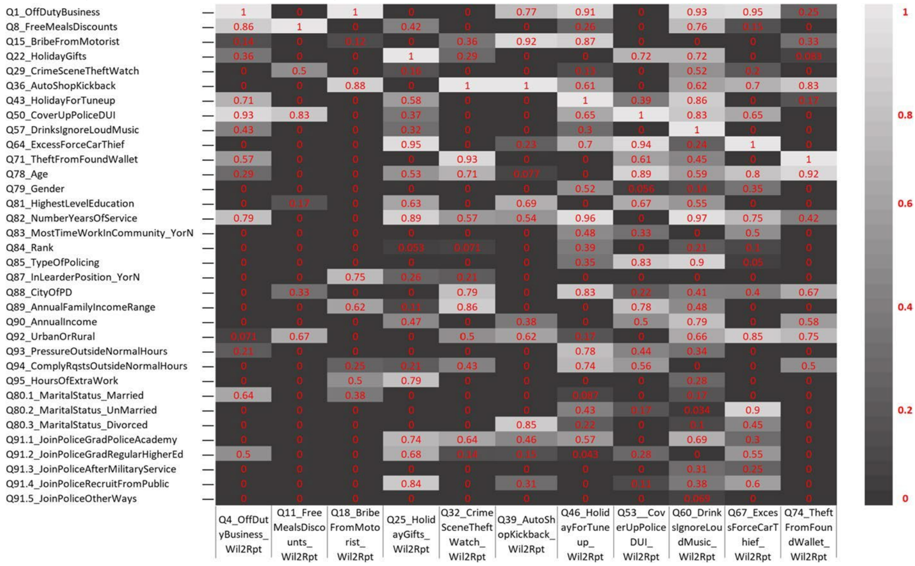

Fig. 1 Heat map summarizing the relative importance of each predictor in the model, as judged by survival time when dropping variables. Values are normalized to 0–1 scale, where 0 cells are not included in the model at all, 1 cells are the variables included in single variable models, and larger values survive longer than smaller values in the same column. Descriptions of Q* variables are shortened for ease of presentation. Column Q* variables were on the Willingness to Report (Wil2Rpt) specific aspects

2019) and the unique opportunity to assess the role of environmental factors on the secrecy code. For example, China has a significant rural–urban divide in many social and economic dimensions, including education, welfare levels, health care, consumption, and housing (Knight et al., 2006). Given the demonstrated influence of societal/community context on police behavioral orientations and police organizational climate (Crank, 2004), the development disparities across regions in China provide an opportunity to observe how the police code of silence operates in different environmental dynamics.

Literature Review

Factors Influencing the Code of Silence

Scholars have noted that the code of silence, as manifested by officers' unwillingness to report fellow officers' misconduct, is one part of police culture and serves as fertile soil that nurtures more severe police misconduct, abuse of power, and police corruption (Crank, 2004; Westley, 1970). This is because, shielded by the code of silence, officers engaging in police misconduct are unlikely to be identified by the police organization and the public and, therefore, can avoid the negative consequences associated with the misconduct. As a function of the secrecy code, the reduced risk of being held accountable for misbehaviors would result in more police misconduct and an escalation of misconduct seriousness.

Given its high relevance to police accountability, in the last few decades, there has been a growing body of research examining the police code of silence across countries (Alain, 2004; Cao et al., 2022; Kutnjak Ivković et al., 2023; Lim & Sloan, 2016; Lobnikar et al., 2016; Torstensson Levander & Ekenvall, 2004; Wu, 2023; Wu & Makin, 2019). It should be noted that most of these studies with a particular focus on the police secrecy code essentially reflect a more significant scholarly effort examining the contours of police integrity in different nations. Using a police integrity scale developed by Klockars and colleagues (2000), scholars have sought to assess police integrity directly by asking about officers' knowledge of official rules governing police behavior, their perceptions of misconduct seriousness, and their likelihood of informing fellow officers engaging in misconduct. These studies have suggested that the police code of silence is a common phenomenon in both centralized and decentralized police systems and in both developed and developing nations (see Kutnjak Ivković et al., 2020; Wu et al., 2018).

Individual Factors

At the individual level, scholars have noted that such demographic characteristics as age, gender, police rank, education, and years of service may influence officers' whistleblowing behavior (Rothwell & Baldwin, 2007; Wu & Makin, 2019). For instance, using a sample of Swedish police officers, Torstensson Levander and Ekenvall (2004) found that older police officers were more willing to report misconduct by fellow officers than their younger counterparts. Given that whistleblowing is a risk-taking behavior (Caldero & Crank, 2011; Crank, 2004), scholars have reasoned that older employees are typically in more powerful positions in their organization and, therefore, have less to fear to blow the whistle (Lee et al., 2004).

For gender differences in the code of silence, studies have yielded mixed results. In a study on police officers in Slovenia, Lobnikar et al. (2016) detected a more substantial code of silence among female officers than their male counterparts. This finding contrasts with an earlier study that found female officers more likely to report fellow officers engaging in misconduct than their male counterparts (Pagon et al., 2000). In explaining these conflicting results, scholars have argued that the gender difference in reporting misbehaviors may need to consider contextual and situational dynamics (Wu & Makin, 2019), as evidence suggests female officers tend to report misbehaviors involving inappropriate use of force. In contrast, male officers tend to report misbehaviors related to the misuse of the position for personal gain. In a recent systematic review of literature on gender disparities in police integrity-related outcomes, Kutnjak Ivković et al. (2023) found no substantial differences in the views about misconduct seriousness and the willingness to report between male and female officers. Regarding the effects of educational attainment on the code of silence, a recent study found that police supervisors with a college degree had a higher likelihood of reporting misconduct by fellow officers than their less-educated counterparts (Lim & Sloan, 2016). However, Truxillo et al.' (1998) longitudinal study suggests that a college degree was not associated with reducing disciplinary problems among officers.

Scholars have also explored the relationship between police rank and police integrity/ the code of silence, obtaining mixed results. While several earlier studies have generally documented that higher-ranked officers were more likely to report fellow officers' misconduct than their lower-ranked counterparts (Kutnjak Ivković, 2012; Ivković et al., 2016b), a recent study showed inconsistent patterns in the influence of rank on officers' perceptions of misconduct seriousness and their willingness to report (Kutnjak Ivković et al., 2019a, b). Using survey data collected from a sample of over 600 officers from 11 U.S. police agencies, Kutnjak Ivković and colleagues (2019a, b) found that while non-supervisors, first-line supervisors, and administrators did not differ significantly in their views about misconduct seriousness and assessments of police misconduct as a rule violation, non-supervisors tended to possess a stronger code of silence than the first-line supervisors and administrators. This finding demonstrates the complexities surrounding the influence of rank. For years of service, findings from prior research suggest a weak relationship between years of service and willingness to report. For instance, in a study on police officers in Québec, Alain (2004) found that although officers with more years of service had a narrower code of silence in terms of reporting minor misbehaviors than their less experienced counterparts, this difference was not detected in reporting more serious misbehaviors. In a study focusing on China, Wu (2018) found that the variable of years of service does not affect Chinese officers' willingness to report fellow officers' misconduct. Scholars have recently begun to examine the linkage between officers' attitudinal orientations and their adherence to the code of silence. For instance, using data collected from Taiwan, Cao et al. (2022) observed that officers' self-recognized integrity was tied to self-control, anti-excessiveforce attitudes, and moral alignment with citizens.

Organizational Factors Research has suggested that officers' willingness to report was influenced by such organizational factors as agency size (Miceli & Near, 1984; Wu et al., 2018) and assignment type (Ivković & Sauerman, 2016). As organizational theorists have pointed out, larger organizations tend to encourage whistleblowing behavior as these organizations are more likely to have procedural arrangements that protect whistleblowers from being unfairly treated (Miceli & Near, 1992). In examining police integrity in South Africa, Ivković and Sauerman (2016) found that traffic police officers evaluate specific misbehaviors as more serious than other police types. Similarly, in a recent study, Wu and Makin (2019) detected a stronger code of silence among criminal investigation police in China, suggesting the influence of assignment type on officers' willingness to report. Scholars have also assessed the influence of organizational self-legitimacy on specific policing outcomes and officers' ethical behaviors (Kutnjak Ivković et al., 2022; Peacock et al., 2023). Their results suggest that while organizational self-legitimacy was a significant organizational predictor of such policing outcomes as trust in the public and job satisfaction (Peacock et al., 2023), its effects on the code of silence were inconsistent across scenarios describing different forms of police misconduct (Kutnjak Ivković et al., 2022).

Environmental Factors Police integrity theorists have argued that police integrity, of which the code of silence is one dimension, is influenced by the social and political environment (Klockars et al., 2004). As Kutnjak Ivković (2015) further noted, "It can be expected that more police agencies of high integrity would be found in the societies that put a high premium on ethical conduct of their governmental employees, rather than in the societies that are more acceptable of misconduct of their governmental employees" (p. 10). Despite this theoretical perspective, scholarly efforts examining the relevance of societal context to police behavior and decision-making remain limited. For the few studies toward this end, some have focused on in-country variations in the code of silence. For example, using a sample of Armenian police officers, Kutnjak Ivković and Khechumyan (2014) found that police officers from the capital city of Armenia expected harsher punishment on those engaging in misconduct than their rural counterparts. Based on survey data collected from China, Wu and Makin (2019) found that officers from agencies in the West of China were less likely to embrace the secrecy code for specific misbehaviors than their counterparts from agencies in the East of China. In a recent study, Wu (2023) found that rural officers in China are more likely to embrace the code of silence than their urban counterparts.

Scholars have also made efforts to explore cross-country variations in the code of silence. For instance, in their comparative analysis, Huberts et al. (2003) found that police officers in the Netherlands were less likely to embrace the code of silence than their American counterparts. Kutnjak Ivković et al. (2020) conducted a recent study investigating the factors linked to the code of silence in Australia, South Africa, South Korea, and the USA. The researchers found that specific societal characteristics, such as corruption levels and the percentage of irreligious citizens in each country, were significant predictors of the code of silence when controlling for the effects of organizational- and individual-level factors. In a recent study based on data collected from China and South Korea, Wu et al. (2022) found a significant country difference (a more substantial code of silence in China than in South Korea) in officers' adherence to the code of silence across all scenarios considered.

The Utility of SVM in the Study of Police Code of Silence

As aforementioned, while police misconduct can be attributable to a wide range of factors (Skolnick, 2005), the secrecy code encourages more serious misconduct, as it protects officers engaging in misbehaviors from internal and external oversight (Crank, 2004; Skolnick, 2002). Given its negative consequences, reducing the secrecy code among police officers is a significant concern for police administrators, policymakers, and the public (Skolnick, 2002). Indeed, showing factors that influence the police code of silence is the first step toward curtailing the code. Although police scholars have argued that police integrity, which includes the code of silence, is a function of individual, operational, organizational, and environmental dynamics, empirical studies examining the influences of factors from these various levels remain limited.

For those available studies, almost without exceptions, either bivariate analysis or regression analysis was used to explore the relationships between explanatory variables and the code of silence. However, as researchers have noted, the observed relationship based on bivariate analysis may be spurious, as it cannot exclude the possibility that both the independent variable and dependent variable are influenced by a third variable that explains away any connections between them (Aldrich, 1995). If assumptions are met, regression analysis is a valuable tool for researchers to examine the relative influences of explanatory variables on the outcome variable using linear models. While linear models are desirable as they are the simplest, relationships between variables could be nonlinear (Krishnamoorthy et al., 2014). Further, as noted by Broussard et al. (2018), regression analysis has limitations in analyzing data related to complex interactions, in which we may be more interested in "identifying distinct subsets and patterns of outcomes" (p. 4). Said another way, a large, noisy, and complex data set may contain multiple clusters (subgroups), and these clusters or subgroups display different patterns on the outcome variable. Clearly, per the nature of regression analysis, it faces a challenge in finding a regression line that best approximates the high dimensional data and may contain multiple clusters (Strobl et al., 2009).

The application of support vector machines (SVMs) allows us to fully engage the dataset and its inherent complexity to predict the willingness of an officer to report a fellow officer. Researchers have noted that police integrity is a complex phenomenon involving multiple dimensions, including knowledge of rules and policies, perceptions of misconduct seriousness, views about potential discipline, and the likelihood of informing (Kutnjak Ivković, 2012). These subdimensions of police integrity may also connect to, as previously reviewed, officers' demographic characteristics (age, gender, educational attainment, rank, years of service, and personal income), organizational factors (agency size and assignment type), and environmental factors (rural/urban area and territorial units). Even more pertinent is the realization that there appears to be initial support concerning the psychometric efficacy of the integrity scale (Alain et al., 2018).

Methods

Sample

Data for this study originated from a larger research project examining police integrity in China collected in 2017. China has three major national police universities, all of which are under the direct leadership of the Ministry of Public Security. The police university where the data was collected offers a variety of programs related to criminal investigation, forensic science, and forensic medicine. In 2018, the university had approximately 6000 enrolled undergraduate and graduate students and provided in-service training programs to approximately 6700 commissioned officers coming from police agencies across the county.

The participants for this study were recruited from those receiving in-service training in the police university. Specifically, the research team obtained permission from the instructors and distributed the paper questionnaires during classes. We used a convenience sampling approach since the tight schedules of the participants did not allow random sampling. Data collection included the respondents' assessment of the seriousness of hypothetical (mis)behaviors, their likelihood to inform and report a fellow officer, and their sociodemographic characteristics. Six hundred-eight responses were collected, yielding a response rate of 91%. It is worth noting that high response rates on the survey questionnaires are standard for studies that collected data from police academies in China (Sun et al., 2010, 2019; Wu et al., 2018), which may be partly attributable to the Chinese cultural context that values collectivism and harmony. Table 1 displays the sample's demographic characteristics, reflecting those predictors included in the model.

Measures

Analytical Plan

Given that our goal is to understand what predicts the willingness to report, we implement support vector machines (SVMs), a machine learning classification method for binary classification problems (Schölkopf et al., 1999). An SVM takes its training data and finds an *optimal* hyperplane separating the two data classes. An optimal hyperplane maximizes the distance between the hyperplane and the nearest data points on each side, i.e., it finds the widest gap between the two classes while minimizing a penalty for misclassified points. The machine classifies future data points based on which side of the hyperplane it falls on.

For data that is not cleanly separable by a *linear* hyperplane, SVM allows the mapping of data in a possibly nonlinear fashion into higher dimensions to make identifying a separating hyperplane possible. This mapping is known as the *kernel trick*, and several options are available for the kernel type, including linear, polynomial, and radial basis functions.

Item	%/Mean (SD)	% Missing
Age (min. = 21; max. = 59)	37.7 (7.60)	3.8
Male	95.2	.5
Married	86.6	.5
Education attainment		.3
High national diploma or below	19.8	
College graduate or above	80.2	
Years of service (min. = 0; max. = 38)	14.3 (8.7)	1.5
Criminal investigation police	61.4	4.1
Work in the community	11.8	.8
Supervisor	28.7	1.5
Annual personal income (RMB)		1.2
Up to 39,999	13.8	
40,000–59,999	37.4	
60,000–79,999	19.1	
80,000–99,999	12.1	
100,000 or above	17.5	
The route joining the police		.5
From police college	45.8	
From regular college	19.2	
From Military	10.2	
Recruitment is open to the public	18.0	
Other	6.8	
Agency location		2.1
East of China	37.8	

Table 1 Descriptive statistics for sample ($N = 608$)

Middle of China	18.2	
West of China	44.0	
Pressure to work overtime (1–6)		1.2
No pressure at all	6.5	
Very low pressure	7.5	
Low pressure	13.3	
Moderate pressure	30.1	
High pressure	26.6	
Very high pressure	16	
Compliance with extra work request (1–4)		1.2
Never	.5	
Sometimes	3.5	
Frequently	44.3	
Always	51.7	

We identify the type of kernel that performs best (along with values of associated parameters) using cross-validation on the data, thus ensuring no overfitting.

Classifier models built by SVM come with a notion of robustness that may not accompany standard approaches using, e.g., regression. The hyperplane separates both data classes equally, and the more significant this separation, the lesser the chance of misclassifying a test instance. Moreover, the ability to consider various nonlinear kernels ensures that the most accurate classifier model is constructed.

Since an SVM optimizes a function that balances maximizing the width of separation of the two classes with minimizing the penalty for misclassification, we use a parameter to determine how much weight to give to the misclassification penalty. The parameter C, also presented as the inverse of the parameter α in some manuscripts and implementations, is the regularization parameter determining how strict of a penalty to apply to misclassifications. A high value of C gives a minor penalty for misclassifications, while a low value gives a higher penalty. We used the Scikit Learn implementation of the standard SVM algorithm for our computations (Pedregosa et al., 2011).

Model Parameters

We select several parameters for each model.

- *Kernel*: This determines what preprocessing (if any) the model does before finding an optimal hyperplane. With linear, no preprocessing is done. The other kernels determine the nonlinear strategy used to map points into higher dimensional space.
- *Gamma*: This intuitively determines the area influenced by any particular data point. Low gamma values mean each point influences a wide area, while high values limit reach. This applies to radial basis functions, polynomials, and sigmoid kernels.
- *Class Weight*: If included, these values weigh examples of rarer classes more highly than standard classes.

We employed a grid search for training our models: we chose ranges of applicable values for each parameter divided into grids, then tried all combinations of those parameter values and selected the model with the best score (see details below) as our selected model.

Matthews Correlation Coefficient

An essential feature within SVM is that we need a way to compare the quality of various candidate models being considered. Usually, we compare one or more statistics on model performance and consider the model with the higher score to be better. While there are many possible statistics to use, with different statistics being more useful depending on the application, some are generally more informative than others. For instance, it may be tempting to compare the percentage of accurate classifications on a testing set, but if we have a training set composed of 90% rabbits and 10% squirrels, a machine that classifies everything as rabbits will have a 90% accuracy even though it is not a particularly good model.

The Matthews Correlation Coefficient (MCC) is a statistic for a binary classification system that judges model quality. Ranging from -1 to 1, MCC values near 0 correspond to models no better than random guessing. Values near -1 or 1 represent strongly predictive models (albeit requiring all predictions to be flipped in the negative case). The main advantage of MCC over other popular statistics, for instance, the F1 score, is that it covers all four quadrants of the confusion matrix: True Positives, False Positives, True Negatives, and False Negatives. This makes it more sensitive to unbalanced class sizes than other such scores.

Since our class sizes are often unbalanced, previous versions of our experiment based on training to maximize F1 score produced models that classified all instances as larger and made no predictions of the smaller class. Training to maximize MCC prevents such uninformative models from being ranked high. Because of these advantages, we use the MCCs of models on our training data to select the best model (Chicco, 2017; Chicco & Jurman, 2020).

Training-Test Split

A machine learning model is said to be overfitted to its training data when it has learned the details of its training data so well that it achieves almost perfect scores in training, but its accuracy on new data suffers. It is the exact error encountered by students who study for an exam by studying a practice exam and then taking the same practice exam to determine if they are prepared for the test. They learn the answers to the practice exam's questions perfectly but do not have the general knowledge of the subject required to tackle new questions. A better approach for such students would be to study a practice exam (or, better yet, several) but hold a different practice exam back and avoid studying it. They can be confident for the actual test when they have studied their training material sufficiently to do well on the reserved exam.

This solution is the way we train most machine learning models. Instead of training on all the data we can find, we split the data into a training set and a testing set. The training set informs our model, and then we try it on the testing set to judge how well it does on new data. Ideally, we go even further and split our data into training, testing, and validation sets. We train our models on the training data until they do well on the testing data, then try them on the validation set to judge how well they do on *new* data. This approach also prevents the model from tweaking hyper-parameters to overfit the testing set.

However, this solution has a problem: when we reserve enough data to build adequate testing and validation sets, we may not provide our model with enough training data to learn. This problem is addressed through cross-validation.

k-fold Cross-Validation

When training a model with k-fold cross-validation, we split the training data into k sets of approximately equal size, called *folds*, and numbered $1, 2, \ldots, k$. We construct models indexed $1, \ldots, k$, where the model labeled i is trained on all but the ith fold. We then test model i on the ith fold data as a test. As our best estimator, we selected the model with the highest score in this test step. We then use this model on the test set to report its final score.

Method of Dropping Variables

Motivated by the desire to build sparse models, our goal was to identify a *good subset* of variables to use in our best model that predicts the outcome of a particular question. While classical regression analysis comes with standard approaches for variable selection, e.g., stepwise regression or the LASSO (Heinze et al., 2018), we implement variable selection directly in our SVM framework. Attempting to use a grid search to find the best set of predictor variables becomes too computationally expensive since it involves doing $2^{\text{(number of variables)}}$ grid search operations, which can be quite an expensive prospect.

We narrowed the search by finding the best model for the complete set of predictor variables and then finding the variable that, when dropped, produced the best model. We then repeated this operation on that selected model. This gives us a reasonable estimate of the order of importance of the predictor variables. Furthermore, it allows us to select the best model of such construction. While we cannot guarantee this is the best possible model, we still find better models than if we used the complete variable set.

Recoding the Data to be Commensurate with SVM

This paper analyzes a dataset of answers to the police integrity questionnaire given to police officers in China. In the first section, the questionnaire describes a scenario in which a police officer does something against regulations, such as accepting a bribe, beating an already subdued suspect, or taking money from a lost wallet. Respondents are then asked to rate the severity of the offense and their likelihood of reporting another officer committing such an infraction, rated on a scale of 1 (low/unlikely) to 5 (high/likely). The second section asks respondents to answer several questions on demographics. These are a combination of binary, ordinal, and categorical data. Because we need numerical data for an SVM to work, all our questions have their answers coded numerically.

Since an SVM interprets numeric information as continuous rather than categorical, we re-coded our categorical variables to avoid this confusion. To this end, we replace any questions with categorical answers with several binary questions. For instance, one of the demographic questions asks about single, married, or divorced marital status. We replaced this question with three questions: “Is the respondent single?,” “Is the respondent married?,” and “Is the respondent divorced?” Each is answered with 0–1 yes–no coding, with the understanding that exactly one of the three has a positive response (i.e., a response of 1). This is a standard approach for working with categorical variables in machine learning models (Chicco, 2017; Schölkopf et al., 1999).

After breaking categorical questions into separate binary questions, there are 34 predictive variables (11 based on the severity of specific scenarios and 23 demographic questions) and 11 questions to predict (the “likelihood to report” questions). We present a more detailed summary of the individual questions in Tables 1, 2, and 3. After discarding responses that failed to record an answer to any of the questions, we had 513 responses to consider. We used a 75%/25% training/testing split.

Results

Best predictive models were identified (from among all models created) for each reportlikelihood question. The resulting models were of varying levels of quality, though all were statistically significant. These models can be used to determine whether the likelihood of reporting reaches our high-quality threshold. Results show a collection of predictive variables for each question that gave the optimal predictive performance, summarized in

Table 4. The necessary questions differed between scenarios; some were more generally applicable between scenarios than others. Note that due to the large sample size, we were able to use in this experiment, we had significant *p*-values for the MCC for all our models, even those with weaker correlations.

Table 2 Assessmentofseriousnessbyscenario($N = 608$)

VariableLabel	Scenario	1 (Notatallserious)(%)	2 (%)	3 (%)	4 (%)	5 (Veryserious) (%)	Mean(*SD*)
Q1	Off-DutySecuritySystemBusiness	23.2	19.3	22.2	13.2	22.1	2.9(1.5)
Q8	FreeMeals,DiscountsonBeat	16.3	21.1	27.8	17.3	17.5	3.0(1.3)
Q15	BribefromSpeedingMotorist	1.8	2.5	8.6	15.8	71.3	4.5(.9)
Q22	HolidayGiftsfromMerchants	32.7	24.0	22.9	10.2	10.2	2.4(1.3)
Q29	CrimeSceneTheftofWatch	0.8	1.2	1.3	6.8	89.9	4.8(.6)
Q36	AutoRepairShop5%Kickback	4.9	8.4	22.4	24.4	39.9	3.9(1.2)
Q43	Supervisor:HolidayforTune-up	13.7	12.6	26.6	21.2	26.0	3.3(1.3)
Q50	Cover-UpofPoliceDUIAccident	27.9	21.0	22.3	12.2	16.7	2.7(1.4)
Q57	DrinkstoIgnoreLoudMusicfromaBar	16.7	19.5	24.2	21.0	18.5	3.1(1.3)
Q64	ExcessiveForceonCarThief	33.6	23.2	19.2	11.8	12.2	2.5(1.4)
Q71	TheftfromFoundWallet	3.5	4.8	13.0	19.1	59.6	4.3(1.1)

DUI drivingundertheinfluence

Table 3 Assessment of willingness to report by scenario ($N = 608$)

Variable Code	Scenario	1 (Definitely not) (%)	2 (%)	3 (%)	4 (%)	5 (Definitely yes) (%)	Mean (*SD*)
Q4	Off-Duty Security System Business	70.9	16.0	8.4	2.0	2.6	1.5(.93)
Q11	Free Meals, Discounts on Beat	62.3	20.5	10.4	3.6	3.1	1.7(1.0)
Q18	Bribe from Speeding Motorist	31.8	19.6	18.6	12.4	17.6	2.6(1.5)
Q25	Holiday Gifts from Merchants	68.9	15.4	10.4	2.8	2.5	1.6(1.0)
Q32	Crime Scene Theft of Watch	17.0	11.4	16.0	16.7	38.8	3.5(1.5)
Q39	Auto Repair Shop 5% Kickback	30.4	20.5	21.5	12.2	15.4	2.6(1.4)
Q46	Supervisor: Holiday for Tune-up	42.7	20.9	19.4	7.3	9.8	2.2(1.3)
Q53	Cover-Up of Police DUI Accident	63.0	15.9	12.2	5.0	4.0	1.7(1.1)
Q60	Drinks to Ignore Loud Music from a Bar	48.6	21.1	15.8	8.2	6.3	2.0(1.2)
Q67	Excessive Force on Car Thief	67.2	16.1	8.8	4.6	3.3	1.6(1.0)
Q74	Theft from Found Wallet	26.0	19.2	19.4	13.3	22.1	2.9(1.5)

DUI driving under the influence

Table 4 Best models identified for each question. Includes the kernel, number of included variables, F1 score, MCC, value of *C*, and the *p*-value for the MCC. Models with MCC > 0.5 are listed in bold—these are the *best* models

Question		Kernel	Vars	F1	MCC	C	*p*-value
Q4	**1- Off-Duty Security System Business**	**Linear**	**14**	**0.674**	**0.541**	**3.0**	$\mathbf{2.161 \times 10^{-11}}$
Q11	2- Free Meals, Discounts on Beat	Linear	6	0.646	0.429	5.0	2.181×10^{-07}
Q18	3- Bribe from Speeding Motorist	Linear	8	0.728	0.349	10.0	2.702×10^{-05}
Q25	**4- Holiday Gifts from Merchants**	**Linear**	**19**	**0.708**	**0.542**	**50.0**	$\mathbf{1.958 \times 10^{-11}}$
Q32	5- Crime Scene Theft of Watch	Linear	14	0.860	0.456	50.0	3.167×10^{-08}
Q39	6- Auto Repair Shop 5% Kickback	Linear	13	0.831	0.458	5.0	2.727×10^{-08}
Q46	**7-Supervisor: Holiday for Tune-up**	**rbf**	**23**	**0.832**	**0.557**	**1.0**	$\mathbf{4.309 \times 10^{-12}}$
Q53	**8- Cover-Up of Police DUI Accident**	**rbf**	**18**	**0.781**	**0.639**	**3.0**	$\mathbf{2.404 \times 10^{-16}}$
Q60	**9- Drinks to Ignore Loud Music from a Bar**	**rbf**	**29**	**0.817**	**0.593**	**50.0**	$\mathbf{8.219 \times 10^{-14}}$
Q67	**10- Excessive Force on Car Thief**	**Linear**	**20**	**0.757**	**0.620**	**1.0**	$\mathbf{3.006 \times 10^{-15}}$
Q74	11- Theft from Found Wallet	rbf	12	0.851	0.451	50.0	4.585×10^{-08}

Perceptions of Seriousness

We judged the relative importance of predictors in the best model for each question based on the order in which they were discarded. The predictor discarded last was considered the most important, while the predictor to be discarded first was considered the least important. Figure 1 is an illustration of the results as a heat map. Lighter shading reflects variables with higher survival, meaning these variables are better at predicting the likelihood of reporting. For most scenarios (and for all our best predictors), the most important predictor was, as might be expected, the perception of the seriousness of the scenario described. In what follows, we focus on the analysis of each scenario, examining to what extent perceptions of seriousness (PoS) individual, environmental, operational, and organizational factors predict the willingness to report a fellow officer. Each deconstruction includes the specific wording of the scenario and a detailed breakdown of the significant predictors. The analysis is presented in this format to demonstrate why tailoring interventions might be a more effective means of improving ethical behavior, as opposed to focusing on solely ethical behavior more generally. These scenarios exist on a continuum of behaviors that, in some areas, would be no violation or a minor infraction to what is clearly criminal behavior.

Case 1. A police officer runs his own private business in which he sells and installs security devices, such as alarms, special locks, etc. He does this work during his off-duty hours. We consider Perception of Seriousness (Q1) and Willingness to Report (Q4).

Fourteen variables successfully predicted the willingness to report an officer for running a private business. While the PoS of the behavior is the most significant predictor, results reveal additional PoS predictors associated with the willingness report, and many of those predictors display higher survival times. Specific to the PoS of other behaviors, the PoS associated with covering up a DUI involving a fellow officer (0.93), accepting free meals while on duty (0.86), accepting a quid-pro-quo solicitation from a supervisor (0.71), not reporting a found wallet (0.57), accepting a bribe to ignore a violation (0.43), accepting holiday gifts (0.36), and seeking a bribe from a speeding motorist (0.14) successfully predict the willingness to report a fellow officer.

Specific to the individual, operational, organizational, and environmental predictors, years sworn (0.79) is an influential predictor with a high survival rate, closely followed by officers who are married (0.64). Specific to operational predictors, those pressured to work overtime (0.21) significantly predict the willingness to report. Lastly, rural location (0.07) was a significant predictor. Concerning the pathway to the police service, higher education (0.50) successfully predicted the willingness to report.

Case 2. A police officer routinely accepts free meals, cigarettes, and other items of small value from merchants on his beat. He does not solicit these gifts and is careful not to abuse the generosity of those who give gifts to him. We consider Seriousness (Q8) and Willingness to Report (Q11).

Six variables successfully predicted the willingness to report an officer for accepting free meals, cigarettes, and other items of small value on their beat. Of the eleven scenarios, only three PoS successfully predicted the willingness to report. As aforementioned, the PoS of the behavior is the most significant predictor, though two other PoS successfully predict the willingness to report: covering up a fellow officer's DUI accident (0.83) and theft from a crime scene (0.50). Level of education (0.17) is the only individual-level predictor with a low survival rate. The remaining significant predictors are environmental variables associated with where the officer works. Most notably, those working in rural locations (0.67).

Case 3. A police officer stops a motorist for speeding. The officer agrees to accept a personal gift of half of the fine in exchange for not issuing a citation. We consider Seriousness (Q15) and Willingness to Report (Q18).

Eight variables successfully predicted the willingness to report an officer for accepting a bribe from a speeding motorist. As aforementioned, while the PoS of this behavior is a significant predictor, it displays the shortest survival rate (0.12)—a result of extreme skewness in that most officers deem the behavior as serious. However, as displayed in Table 3, there is variability across the willingness to report a fellow officer. Interestingly, the PoS with the highest survival rate, the most significant predictor, relates to taking part in a kickback scheme with an auto repair shop (0.88). Organizationally, those in supervisory positions (0.75), those complying with requests to work overtime (0.25), and those working higher overtime hours (0.50) successfully predicted the willingness to report. The remaining predictors are individual-level characteristics, including those with higher family annual income (0.62) and married (0.38).

Case 4. A police officer is widely liked in the community. On holidays, local merchants and restaurant and bar owners show their appreciation for his attention by giving him gifts of food and liquor. We consider Seriousness (Q22) and Willingness to Report (Q25).

Nineteen variables successfully predicted the willingness to report an officer for accepting holiday gifts from merchants. Of the eleven scenarios, seven of the PoS successfully predicted the willingness to report a fellow officer. As aforementioned, the PoS of the behavior is the most significant predictor. Additionally, the PoS associated with excessive force on a car thief (0.95) survives nearly as long as the scenario PoS. Relatedly, the PoS for accepting a quid-pro-quo solicitation from a supervisor (0.58), accepting free meals or a discount on the beat (0.42), covering up a DUI involving a fellow police officer (0.37), accepting a bribe from a local establishment for violating a noise ordinance (0.32), and stealing a watch from a crime scene (0.16) are significant predictors for willingness to report. Individual level predictors include age (0.53), level of education (0.63), years sworn (0.89), annual family income (0.11), and personal income (0.47). Organizationally, those in supervisory positions (0.26), those complying with requests to work overtime (0.21), working more extra hours (0.79), and rank (0.05) successfully predicted the willingness to report. Concerning the pathways to the police service, academy (0.74), higher education (0.68), and those recruited from the general public (0.84) displayed high levels of survival when predicting the willingness to report.

Case 5. A police officer discovers a burglary of a jewelry shop. The display cases are smashed, and it is evident that many items have been taken. While searching the shop, he takes a watch worth about two days' pay for that officer. He reports that the watch had been stolen during the burglary. We consider Seriousness (Q29) and Willingness to Report (Q32).

Fourteen variables successfully predicted the willingness to report an officer for stealing a watch from a crime scene. Of the eleven scenarios, four of the PoS successfully predicted the willingness to report a fellow officer: finding a wallet with a full day's pay and keeping the money (0.93), accepting a bribe from a speeding motorist (0.36), and accepting holiday gifts from merchants (0.29). Age (0.71), years sworn (0.57), and annual family income (0.86) were strong individual-level predictors of the willingness to report. Two pathways to the police service successfully predicted the willingness to report, including the academy (0.64) and higher education (0.14). There are several operational, organizational, and environmental predictors predicting the willingness to report, including rank (0.07), those in a supervisory position (0.21), location (0.79), officers working in a rural location (0.50), and those who comply with requests to work overtime (0.43).

Case 6. A police officer has a private arrangement with a local auto body shop to refer the owners of cars damaged in accidents to the shop. In exchange for each referral, he receives payment of 5 percent of the repair bill from the shop owner. We consider Seriousness (36) and Willingness to Report (Q39).

Thirteen variables successfully predicted the willingness to report an officer for participating in a kickback scheme with an auto repair shop. Of the eleven scenarios, four PoS successfully predicted the willingness to report a fellow officer. In addition to the PoS associated with the scenario, PoS for accepting a bribe from a speeding motorist (0.92), running an off-duty security business (0.77), and observing excessive force on a car thief (0.23) successfully predicted the willingness to report. Five individual-level variables predicted the willingness to report, including age (0.07), years sworn (0.54), being divorced or separated (0.85), level of education (0.69), and personal income (0.38). Rural location (0.62) is the only environmental level variable successfully predicting the willingness to report. Specific to the pathway to the police service, the academy (0.46), higher education (0.15), and those recruited from the general public (0.31) were successful predictors.

Case 7. A police officer, who happens to be a very good auto mechanic, is scheduled to work during coming holidays. A supervisor offers to give him these days off if he agrees to tune up his supervisor's personal car. Evaluate the supervisor's behavior. We consider Seriousness (43) and Willingness to Report (Q46).

Twenty-three variables successfully predicted the willingness to report a supervisor for offering a quid-pro-quo solicitation to a subordinate. Of the eleven scenarios, nine PoS successfully predicted the willingness to report the supervisor. Neither the PoS for accepting holiday gifts or finding a wallet with a full day's pay and keeping the money predicted the willingness to report. Several individual-level variables successfully predicted the willingness to report, including male officers (0.52), years sworn (0.96), and marital status (married (0.08), single (0.43), divorced or separated (0.22)). Working in the community (0.48), location (0.83), and rural (0.17) were environmental-level variables successfully predicting willingness to report. Three operational-level variables were successful predictors, including policing type (0.35), pressure to work overtime (0.78), and compliance with requests to work overtime (0.74). Rank (0.39) also successfully predicted the willingness to report. Concerning the pathway to the police service, the academy (0.57) and higher education (0.04) predicted the willingness to report.

Case 8. At 2:00 a.m., a police officer, who is on duty, is driving his patrol car on a deserted road. He sees a vehicle that has been driven off the road and is stuck in a ditch. He approaches the vehicle and observes that the driver is not hurt but is obviously intoxicated. He also finds that the driver is a police officer. Instead of reporting this accident and offense, he transports the driver to his home. We consider Seriousness (Q50) and Willingness to Report (Q53).

Eighteen variables successfully predicted the willingness to report an officer for covering up a DUI involving a fellow police officer. Of the eleven scenarios, five of the PoS successfully predicted the willingness to report a fellow officer. In order of survival, the PoS for observing excessive force on a car thief (0.94), accepting holiday gifts from merchants (0.72), finding a wallet with a full day's pay and keeping the money (0.61), and accepting a quid-pro-quo solicitation from a supervisor (0.39) successfully predicted the willingness to report. Six individual-level variables successfully predicted the willingness to report, including age (0.89), male (0.05), married (0.17), level of education (0.67), annual family income (0.78), and personal income (0.50). There were several environmental and operational predictors associated with the willingness to report, including working in the community (0.33), location (0.22), police type (0.83), pressure to work overtime (0.44), and compliance with requests to work overtime (0.56). Lastly, higher education (0.28) and those recruited from the general public (0.11) were pathways to the police service, successfully predicting the willingness to report.

Case 9. A police officer finds a bar on his beat that is still serving drinks a half-hour past its legal closing time. Instead of reporting this violation, the police officer agrees to accept a couple of free drinks from the owner. We consider Seriousness (Q57) and Willingness to Report (Q60).

Twenty-nine variables successfully predicted the willingness to report an officer for accepting a bribe from a local establishment for violating a noise ordinance. Of the eleven scenarios, only one PoS successfully predicted the willingness to report a fellow officer. The exception is the PoS associated with accepting a bribe from a speeding motorist, which, as you may recall, was universally deemed a severe offense. Specific to the individual, environmental, and operational-level variables, only working in a community, holding a supervisory position, compliance with requests to work overtime, and higher education as a pathway to the police service failed to predict the willingness to report.

Case 10. Two police officers on foot patrol surprise a man who is attempting to break into an automobile. The man flees. They chase him for about two blocks before apprehending him by tackling him and wrestling him to the ground. After he is under control, both officers punch him a couple of times in the stomach as punishment for fleeing and resisting.
We consider Seriousness (Q64) and Willingness to Report (Q67).

Twenty variables successfully predicted the willingness to report an officer for excessive force on a car thief. Of the eleven scenarios, six of the PoS successfully predicted the willingness to report a fellow officer. Specifically, running an off-duty security business (0.95), accepting free meals or a discount on the beat (0.15), stealing a watch from a crime scene (0.20), taking part in a kickback scheme with an auto repair shop (0.70), and covering up a DUI involving a fellow police officer (0.65) successfully predicted the willingness to report. Several individual-level variables successfully predicted the willingness to report. Those include age (0.80), male (0.35), single, unmarried (0.90), divorced, separated (0.45), and years sworn (0.75). Environmental predictors included those working in the community (0.50) and classified as rural (0.85). Operational predictors included those in a supervisory position (0.40) and police type (0.05). Lastly, rank (0.10) predicted the willingness to report. Concerning the pathway toward the police service, academy (0.30), higher education (0.55), military route to joining the police (0.25), and from the general public route (0.06), pathways predicted the reporting of a fellow officer.

Case 11. A police officer finds a wallet in a parking lot. It contains an amount of money equivalent to a full day's pay for that officer. He reports the wallet as lost property but keeps the money for himself. We consider Seriousness (Q71) and Willingness to Report (Q67).

Twelve variables successfully predicted the willingness to report an officer for finding a wallet with a full day's pay and keeping the money. Of the eleven scenarios, six of the PoS successfully predicted the willingness to report a fellow officer. In addition to the PoS associated with the scenario, PoS for running an off-duty security business (0.25), accepting a bribe from a speeding motorist (0.33), accepting holiday gifts from merchants (0.08), taking part in a kickback scheme with an auto repair shop (0.83), and accepting a quid-pro-quo solicitation from a supervisor (0.17) successfully predicted the willingness to report. Few individual, environmental, and operational-level variables successfully predicted the willingness to report. Included are age (0.78), personal income (0.58), years sworn (0.42), location (0.67), rural (0.75), and compliance with requests to work overtime (0.50).

Summary of Predictors

As displayed in Fig. 2, the results of our analysis reveal high survivable variables (> 0.50) that successfully predict the willingness to report a fellow officer. Categorically, the most significant predictors are associated with the perceptions of seriousness (PoS), closely

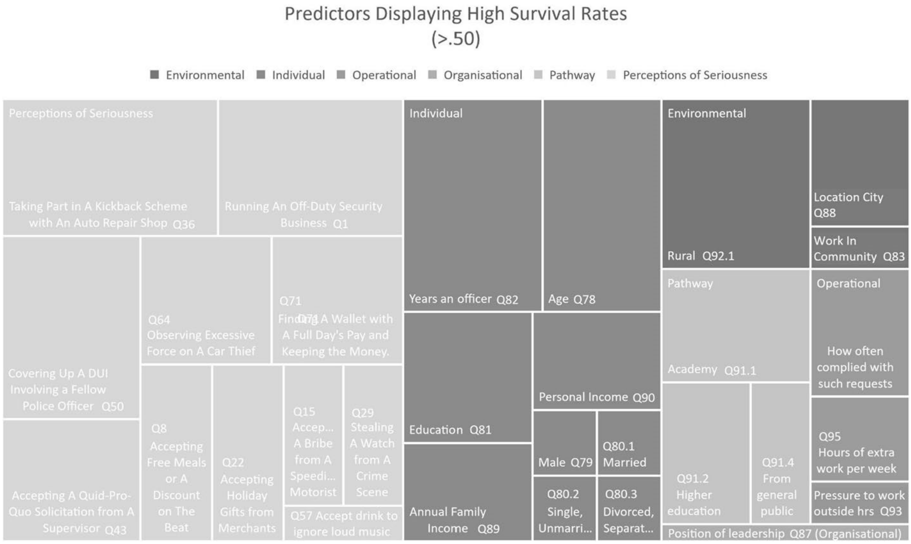

Fig. 2 Heat map summarizing the relative importance of each predictor in the model displaying high survival rates (> 0.50). The bigger a box, i.e., the greater its size/area, the higher the survival rate of that variable. The subgroup heading is listed at the top of a box of a variable in that subgroup. In contrast, individual variable names are listed at the bottom, justified inside their respective boxes. Their corresponding Q* numbers are also listed (see Table 5 for a listing)

followed by Environmental, Individual, Operational, Pathway to the Police Service, and Organizational predictors. See Table 5 for a listing of the subgroup (or category) that each variable belongs to. Forty-two PoS successfully predicted the willingness to report across the eleven scenarios. The kickback scheme with an auto repair shop was the most successful predictor influencing the willingness to report in seven scenarios. The least successful PoSs are Accepting a Bribe from a Local Establishment for Violating a Noise Ordinance

Table 5 Variable code with a brief description for each predictor and the subgroup that it belongs to. See Fig. 2 for their relative importances. Variables shown in columns of Fig. 1 are the Willingness to Report versions of the 11 Perceptions of Seriousness questions (in the same order as listed here), for which predictive models are built

Predictor	Subgroup
Q1_OffDutyBusiness	Perceptions of Seriousness
Q8_FreeMealsDiscounts	Perceptions of Seriousness
Q15_BribeFromMotorist	Perceptions of Seriousness
Q22_HolidayGifts	Perceptions of Seriousness
Q29_CrimeSceneTheftWatch	Perceptions of Seriousness
Q36_AutoShopKickback	Perceptions of Seriousness
Q43_HolidayForTuneup	Perceptions of Seriousness
Q50_CoverUpPoliceDUI	Perceptions of Seriousness
Q57_DrinksIgnoreLoudMusic	Perceptions of Seriousness
Q64_ExcessForceCarThief	Perceptions of Seriousness
Q71_TheftFromFoundWallet	Perceptions of Seriousness
Q78_Age	Individual
Q79_Gender	Individual
Q80.1_MaritalStatus_Married	Individual
Q80.2_MaritalStatus_UnMarried	Individual
Q80.3_MaritalStatus_Divorced	Individual
Q81_HighestLevelEducation	Individual
Q82_NumberYearsOfService	Individual
Q83_MostTimeWorkInCommunity_YorN	Environmental
Q84_Rank	Individual
Q85_TypeOfPolicing	Organisational
Q87_InLearderPosition_YorN	Organisational
Q88_CityOfPD	Environmental
Q89_AnnualFamilyIncomeRange	Individual
Q90_AnnualIncome	Individual
Q91.1_JoinPoliceGradPoliceAcademy	Pathway
Q91.2_JoinPoliceGradRegularHigherEd	Pathway
Q91.3_JoinPoliceAfterMilitaryService	Pathway
Q91.4_JoinPoliceRecruitFromPublic	Pathway
Q91.5_JoinPoliceOtherWays	Pathway
Q92_UrbanOrRural	Environmental
Q93_PressureOutsideNormalHours	Operational
Q94_ComplyRqstsOutsideNormalHours	Operational
Q95_HoursOfExtraWork	Operational

(PoS holding a high survival rate for only this scenario), bribing a speeding motorist (PoS holding a high survival rate for only two scenarios), and crime scene theft of watch (PoS holding a high survival rate for only two scenarios). Individual-level variables were successful in twenty-seven predictions. The most significant were years as an officer and age, admittedly collinear and associated with high survival rates in seven and six scenarios, respectively. The environmental variables were successful in ten predictions, with rural environments predicting the willingness to report in six scenarios and officers working primarily in the community associated with only one scenario. Pathway to the police service successfully predicted the willingness to report in nine scenarios, with the Academy being the most successful. The military is the pathway to police service, and others have no survival rates above 0.50. Operational predictors displayed high survival rates in six scenarios, with complying with requests to work overtime displaying a high survival rate in three scenarios. Organizational predictors were the least significant, displaying high survivability in only one scenario.

Discussion

Using an innovative approach with the application of support vector machines (SVMs), this study advances our understanding of what factors—from distinct levels including individual, organizational, and environmental—best predict officers' willingness to report misconduct by fellow officers. While the findings highlight the salient influences of officers' perceptions of the seriousness of misconduct on their reporting behavior, these influences vary across scenarios, reflecting different forms of misbehavior. The results also suggest that, though not comparable to the predictive power of perceptions of seriousness, the relevance of several other environmental (e.g., agency location: rural vs. urban) and individual (e.g., years of service, educational attainment) factors to willingness to report is noticeable.

Although much of prior research suggests that officers' adherence to the code of silence is a function of individual, organizational, and environmental dynamics, the results of the current study demonstrate that factors from these different levels vary in their influences on officers' willingness to report (the opposite of the code of silence). As this study revealed, officers' perceived seriousness of misbehavior is considered the most important predictor of the outcome variable. This finding aligns with the results of prior studies (Kutnjak Ivković et al., 2013; Kutnjak Ivković et al., 2019a, b; Wu & Makin, 2019), suggesting a strong linkage between evaluations of misconduct seriousness and the tendency to adhere to the code of silence. As Wu and Makin (2019) noted, it seems reasonable that people tend to report misbehaviors by their coworkers if they view them as serious.

Notwithstanding their overall strong association with willingness to report, the influences of perceptions of seriousness are not homogenous for all scenarios describing different forms of police misbehavior. Indeed, our results demonstrate that officers' assessments of seriousness for certain types of misbehaviors can better predict their willingness to report than do their seriousness assessments for other types of misbehaviors. Specifically, officers' perceptions of seriousness for misbehaviors reflecting ethical dilemmas (e.g., off-duty security system business, supervisor: holiday for a tune-up, and cover-up of police DUI accident) can predict their willingness to report for more scenarios than can the PoSs for misbehaviors that are essentially criminal (e.g., bribe from speeding motorist, and crime scene theft of watch). This result aligns with prior research that found fewer variations in officers' adherence to the code of silence for more serious misconduct (officers generally showed a high willingness to report this type of misconduct (*see* Kutnjak Ivković et al., 2018). This finding has important implications for police training aimed at curtailing the code of silence. It suggests that police administrators could be more effective in reducing the code of silence among their police officers if they provided targeted training emphasizing improving their officers' seriousness perceptions of what are regarded as unethical behaviors rather than those that could be viewed as crimes. Indeed, one critical component of this training should be to increase officers' awareness of official rules governing police behavior, as studies have consistently demonstrated that officers' evaluation of the seriousness of a specific misbehavior was tied to their views about whether it was a violation of official rule or policy (Ivković et al., 2016a, b; Ivković & Sauerman, 2016; Wu et al., 2018). Given that this targeted training will focus on officers' perceptions of unethical behaviors (which may be viewed as those in somewhat grey areas), it seems particularly important to inform officers that these are rule-violating behaviors detrimental to the officer, organization, and community.

This study also demonstrates the role of environmental factors in shaping the police code of silence. Leveraging the unique societal context of China, this study reveals that the variable reflecting the rural/urban setting shows a strong predictive power for willingness to report. Indeed, as mentioned previously, the environmental dynamics of the police code of silence, or more broadly, police integrity, have been less examined in prior empirical research despite related theoretical reasonings suggesting they are essential. This is mainly because prior relevant efforts have primarily focused on Western countries (some transitional societies) with no substantial differences in development levels across regions and between rural and urban areas. The data used in these studies was limited in capturing contextual variations that could affect the code of silence. The findings of this study demonstrate the value of China's context in understanding the dynamics of the police code of silence, as its large rural–urban gap and considerable regional development disparities (a context in which police agencies operate) make *visible* the influence of environmental factors (largely *invisible* in the data collected from developed societies). As such, this study has contributed to advancing theoretical understanding regarding the environmental dynamics of the code of silence.

Indeed, scholars have noted the significant rural–urban divide in China (reflected by the disadvantages in many social and economic dimensions in rural areas (see Knight et al., 2006) and the limited public resources in rural areas. As Wu and Wen (2020) observed, rural police officers in China experienced higher psychological strain than their urban counterparts, possibly because of constraints in resources and training associated with rural policing. Given the evidence suggesting the potential link between stress/strain and adherence to the code of silence (Wu, 2018; Wu & Makin, 2019, 2021) and the relevance of rurality to policing (Page & Jacobs, 2011), it seems not surprising that the rural/urban context plays a significant role in predicting officers' willingness to report fellow officers. The result is consistent with a previous study using data from Taiwan, which found that rural officers in Taiwan showed higher group cohesion than their urban counterparts (Sun & Chu, 2009).

It is worth noting that environmental factors overall perform better than individual-level factors in predicting willingness to report. This finding further highlights the importance of considering environmental dynamics in exploring the antecedents of the code of silence (Wu et al., 2022). As mentioned previously, prior relevant research has predominantly focused on organizational and individual-level factors, which, as this study suggests, is limited in scope to identify important factors shaping the code of silence. However, this study does demonstrate that some individual-level variables, such as years of service, educational attainment, and income, play an essential role in shaping officers' willingness to report. This finding aligns with prior research (e.g., Ivković et al., 2016a, b; Ivković & Sauerman, 2016; Lim & Sloan, 2016) and shows the need to continuously include these individuallevel factors in exploring the police code of silence.

Limitations

This study presents a novel approach to police integrity using support vector machines. While robust, the limitations must be considered when interpreting the study results. First, our dependent variable reflects self-reported measures of the willingness to report a fellow officer. Our prediction reflects a respondent's belief that they would report and cannot account for real-world conditions when an officer decides to report or not report. While we include organizational and operational factors in the predictions, and those factors display significance, our results are best understood as such. Relatedly, we cannot account for the potential of social desirability influencing responses to the Police Integrity Instrument. Second, our sample reflects officers enrolled in the police university for in-service training. As such, our results are not generalizable to all police officers in China. Third, while a sample size of 608 would be considered high within the body of scholarship using the Police Integrity Instrument, convenience sampling further limits the generalizability of the study. On a related note on the size of the data set, while we used cross-validation to avoid overfitting predictive models, evaluating the best models on an external test set would help to make them more robust.

Future Research and Conclusion

As aforementioned, there is a substantial body of research documenting police integrity and the contours of integrity domestically and internationally, and recent research applying a comparative lens. As a standardized instrument, this body of research would benefit from applying machine learning techniques to isolate better the factors predicting police integrity, undermining the code of silence. Given the psychometric properties of the instrument discussed by Alain et al. (2018), researchers must seek collaborations pooling responses, allowing for replication of the current study with a larger, more diverse sample.

As our results suggest, a pathway towards improving integrity could leverage academy curriculum and in-service training emphasizing ethical dilemmas where there are gradations, allowing for deconstructions of decision-making that consider organizational, operational, environmental, and individual factors. Intentional emphasis on ethical gradations can incorporate those existing within the "grey" area, where meaningful conversations can explore the dimensions of direct and indirect pressures inhibiting reporting focusing on organizational incentives and disincentives. The adaption of Active Bystander for Law Enforcement (ABLE) training could be an effective mechanism for targeting behaviors that exist within these "grey" areas and serve to demonstrate a supportive organizational culture—recognized as a critical component for programmatic efficacy for intervention programs (see Banyard et al., 2007; Schindeler, 2014).

Declarations

Competing Interests The authors declare no competing interests.

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