An Exploratory Profiling Study of Online Auction Fraudsters

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Chapter 4

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Abstract Online auctions are one of the most popular e-commerce applications. With the growth of online auctions, the amount of online auction fraud has increased significantly. Little work has focused on the criminal profiling of online auction fraudsters. This exploratory study uses multivariate behavioral analysis to profile 61 online auction fraud offenders based on their behavior. The relationships between offender behavior and personal characteristics are also examined. The results yield a taxonomy of online auction fraud offenders: (i) novice-moderately-active; (ii) intermediate-inactive; and (iii) experienced-active. Discriminant analysis of the personal characteristics of offenders yields 78.6% accurate identification of the offender type. The results demonstrate that (intrinsic) personal motivation, education level and age are the most significant characteristics of experienced-active offenders.

Keywords: Online auctions, criminal profiling, multivariate behavioral analysis

1. Introduction

The growth of online shopping has been phenomenal. Online auctions are one of the most popular online shopping platforms as evidenced by eBay's 19% increase in profits (totaling $677 million) during the first quarter of 2013 alone [11]. The increased popularity of online auction sites has seen a related growth in online auction fraud. According to the U.S. Federal Bureau of Investigation (FBI) Internet Crime Complaint Center (IC3), online auction fraud is consistently among the top complaints, with a high of 71.2% in 2004 [1].

Research on online auction fraud by Dong, *et al.* [4] and Trevathan and Read [15] has focused on the typology of online auction frauds. Pandit, *et al.* [10] have identified online auction fraudsters by analyzing interactions between buyers and sellers. Meanwhile, researchers have ascertained that traditional criminal profiling techniques can be very useful in dealing with different types of cybercrimes [12]. However, empirical studies that apply criminal profiling techniques to real online auction offender data are practically nonexistent.

This paper uses multivariate behavioral analysis to profile 61 online auction fraud offenders. The relationships between offender behavior and personal characteristics identify three types of online auction fraud offenders: (i) novice-moderately-active; (ii) intermediate-inactive; and (iii) experienced-active. The results also demonstrate that (intrinsic) personal motivation, education level and age are the most significant characteristics of experienced-active offenders.

2. Profiling Fraudsters

Casey [3] states that criminal profiling is very useful when little is known about the offenders, which is particularly important because criminals often use the Internet to conceal their identities and activities. Rogers [12] emphasizes the importance of using criminal profiling in cybercrime investigations, but there is no general theoretical model or approach for profiling cybercrime offenders.

Rogers [12] notes that two major criminal profiling approaches are employed by forensic scientists and practitioners: inductive and deductive profiling. An inductive approach is commonly employed by the FBI in profiling traditional crimes; many forensic scientists also adopt an inductive approach in profiling cybercrimes. However, other forensic scientists (e.g., [16]) argue that a deductive approach should be employed in investigating cybercrimes. In particular, they recommend the use of behavioral evidence analysis for cybercrime offender profiling because it is more objective, i.e., it relies more on facts than statistical inferences.

The application of traditional criminal profiling models to cybercrime investigations is an interesting concept. Goodwill, *et al.* [6] have compared three models of offender profiling on a group of (stranger) rapists to help predict the characteristics of offenders. The three models include the power and anger model of Hazelwood [7], the behavioral thematic model of Canter, *et al.* [2], and the MTC:R3 typology [9] with a multivariate approach adapted from [2]. Goodwill, *et al.* [6] recommend a fourth model, multivariate behavioral analysis, which combines clusters of behavior over simple bivariate relationships between individual behavior and background characteristics. In fact, their study concluded that multivariate behavioral analysis yields results that greatly surpass those obtained with the other three models.

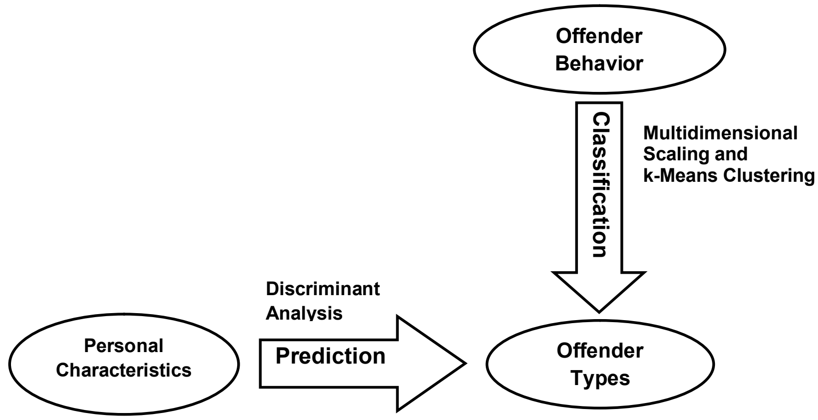

Figure 1. Multivariate profiling approach.

The multivariate profiling approach [6] illustrated in Figure 1 helps understand the underlying factors that can be used to classify offenders, and how personal characteristics may be used to predict the types of offenders. Multivariate analysis has proved to be effective at profiling cybercrimes. Stabek, *et al.* [14] have applied the technique to understand the incidence of scams. Their content analysis technique is similar to that used by Goodwill, *et al.* [6], who leverage hierarchical clustering and discriminant function analysis. Kjaerland [8] has applied multivariate profiling to account for the multitude of features that appear simultaneously in cyber incidents.

This exploratory study applies the multivariate profiling methodology to analyze offender behavior. The relationships between the behavior and personal characteristics of offenders are also examined. The results provide insights into the use of multivariate profiling to create profiles of online auction fraudsters.

3. Profiling Methodology

Aleem and Antwi-Boasiako [1] have developed a taxonomy of eBay auction frauds based on the *modus operandi* of cyber criminals. The frauds include non-delivery of merchandise, failure to pay, counterfeits and reproductions, bid shilling, bid shielding, misrepresentation, fee stacking, shell auctions and phishing, triangulations and fencing, buying and switching, and loss/damage claims. This exploratory study focuses on one type of online auction fraud – counterfeits and reproductions. The reason is that the study is based on the online auction offender database of the Hong Kong Customs and Excise Department, which maintains data pertaining exclusively to counterfeit goods.

Table 1. Offender behavior variables.

Variable	**Description**
S1_Engaged3mLess	Engaged for less than 3 months
S1_Engaged4_6m	Engaged for 4–6 months
S1_Engaged7_12m	Engaged for 7–12 months
S1_Engaged13mAbove	Engaged for more than 13 months
S2_5TxBelow	Less than 5 transactions per month
S2_6_10Tx	Between 6–10 transactions per month
S2_11_30Tx	Between 11–30 transactions per month
S2_31_99Tx	Between 31–99 transactions per month
S2_100TxAbove	More than 100 transactions per month
S3_Earn1kLess	Earned less than HK$1,000 per month
S3_Earn1k_5k	Earned between HK$1,001 to HK$5,000 per month
S3_Earn5kMore	Earned more than HK$5,001 per month
S4_BoughtFromWebsite	Items bought from online websites (e.g., Taobao)
S4_BoughtFromHK_China	Items bought from shops/factories in China/HK
S4_BoughtFromFriends	Items bought from friends or other sources
S5_SeizureValueBelow10k	Total seizure value was less than HK$10,000
S5_SeizureValue10k_50k	Total seizure value was HK$10,001 to HK$50,000
S5_SeizureValueAbove50k	Total seizure value was more than HK$50,001

The online auction offender database contained case reports from 2012 to the middle of 2013. In the study, we assumed that each offender was responsible for his/her offenses, although not all the offenders were convicted of their alleged crimes at the time of the study. The database had 121 cases. Cases with missing data were eliminated, yielding a total of 61 online auction offender cases that were considered in the study. Seven offenders were accused of copyright infringements while 54 were accused of trademark infringements.

3.1 Preparation of Variables

The variables collected from the offender database were divided into two categories: (i) offender behavior variables; and (ii) personal characteristics variables.

All the offender behavior variables were recoded as dichotomous variables to facilitate analysis and interpretation. Variables with multiple categories were dummy coded as multiple dichotomous variables (e.g., variables for the engagement period and source of auction items) and a pool of eighteen variables was created. The eighteen variables and their descriptions are presented in Table 1. Note that all currency values are expressed in Hong Kong dollars (HK$).

The personal characteristics variables are categorized into two conceptual groups: demographic variables (e.g., sex, age and education level) and intrinsic motivation (e.g., reason for engaging in online auction activities and why [the offender was] not afraid of being caught). The personal characteristics variables, their descriptions and other key information are presented in Table 2.

3.2 Analytical Process

The data analysis process involved three steps. First, multidimensional scaling analysis was applied to the eighteen dichotomous offender behavior variables. This technique identified the underlying structure of the offender behavior variables: similar variables formed clusters when the variables were plotted as points in two-dimensional space. The second step performed k-means clustering to classify the offender cases into offender types based on the clusters of offender behavior variables. The final step performed discriminant analysis to check if the offender types could be predicted from the personal characteristics variables.

4. Results

This section describes the multidimensional scaling results and the discriminant analysis results.

4.1 Offender Behavior Variables

Nearly 50% (30 of the offenders were engaged in online auction fraud for periods ranging from four months to twelve months, while 28% (17) and 23% (14) were engaged in online auction fraud for less than three months and more than one year, respectively. The total seizure value was about HK$1 million, but only 5% (3) of the offenders were involved in seizures valued at more than HK$50,000. Most of the offenders (52%) earned less than HK$1,000 per month from online auction fraud activities, with about 16% (10) earning more than HK$5,000 per month. Only 18% of the offenders were actively involved with more than 30 transactions per month; the majority of the offenders were less active with fewer than eleven transactions per month (48%) or moderately active with 11–30 transactions per month (31%). About 80% of the counterfeit goods were sourced from other online websites while the remaining 20% of the goods were bought from factories in Hong Kong or China or bought from other sources.

Table 2. Personal characteristics variables.

Variable	**Description**	**Value**	**Frequency**
Sex	Gender of offender	Female	32.80%
		Male	67.20%
Age	Age of offender	–	Mean = 30
			Min = 18
			Max = 54
Education Level	Education level of offender	Primary or lower	3.30%
		Secondary	63.90%
		Tertiary	13.10%
		University or higher	19.70%
Occupation	Occupation of offender	Unemployed	24.60%
		Student	14.80%
		Employed	55.70%
		Housewife	4.90%
Income Level	Income level of offender	No stable income	14.80%
		Income of HK$9,999 or lower	21.20%
		Income of HK$10,000 to HK$19,999	27.90%
		Income of HK$20,000 or higher	8.20%
		Missing data	27.90%
Economic Status	Economic status of offender	Poor	63.90%
		Average	32.80%
		Rich	3.30%
Marital Status	Marital status of offender	Single	63.90%
		Married	27.90%
		Divorced	8.20%
Living Status	Living arrangement of offender	Lived alone	4.80%
		Lived with parents	63.90%
		Lived with spouse or friend	31.30%
Arrest History	Previous arrests of offender	No arrest history	90.20%
		Related fraud arrest history	4.20%
		Non-related arrest history	5.60%
Objective	Reason for engaging in online auction activities	Monetary	78.90%
		Thrill	21.10%
Why not afraid of being caught	Why the offender was not afraid of being caught by the Customs and Excise Department	Believed would not get caught easily	42.60%
		Did not know it was an offense	49.20%
		Did not disclose	8.20%

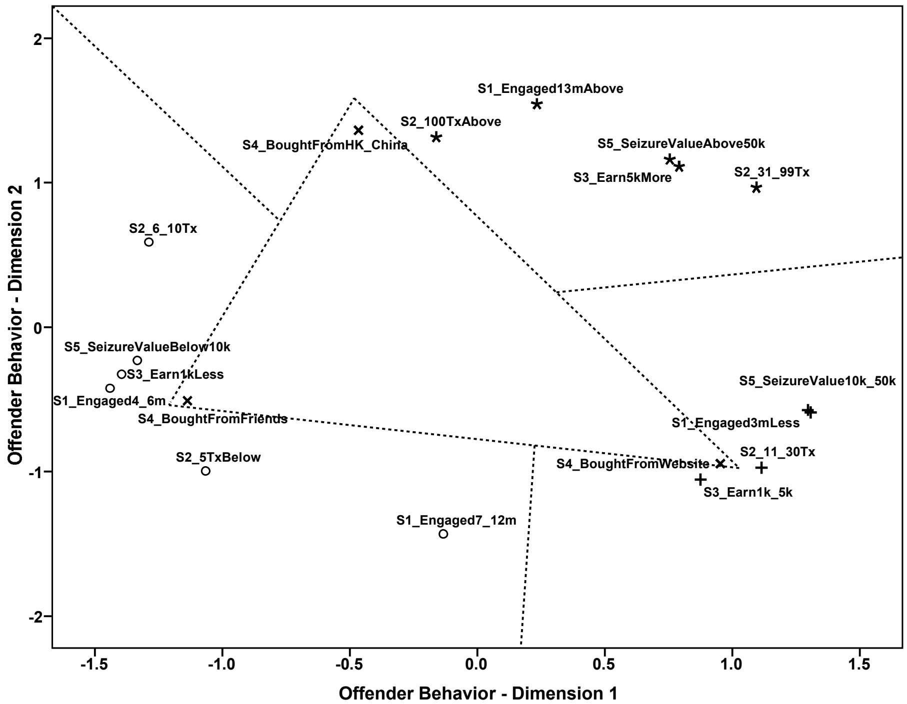

Figure 2. Multdimensional scaling plot of the offender behavior variables.

4.2 Personal Characteristics Variables

Table 2 provides detailed information about the personal characteristics variables. The personal characteristics variables reveal that most of the offenders were male (67%), single or divorced (72%), lived with their parents (64%) and were between the ages of 22 and 39 (68%). Most of the offenders had secondary school education (64%) and were employed (56%), but were relatively poor (64%) with only 8% (5) of them earning more than HK$20,000. Nearly all the offenders (90%) did not have a previous arrest history. Most of them (79%) were engaged in online auctions for monetary reasons (e.g., to improve their living standards). About half the offenders (49%) said that they did not know that the goods they sold were counterfeit.

4.3 Multidimensional Scaling Results

The two-dimensional coordinates for the 18 offender behavior variables were hierarchically clustered using Ward's Method with the squared Euclidean distance and standardized Z-score. Figure 2 shows the results with regional hierarchical clustering of scaling coordinates. Three clusters of offender behavior variables were identified; they are marked in Figure 2. The three clusters divide the two-dimensional space of offender behavior variables into three non-overlapping areas and one common central region. The three clusters correspond to the following three offender types:

- **Offender Type 1 (Novice-Moderately-Active):** This cluster is marked with a "+" in Figure 2. Variables at the right end of Dimension 1 and the bottom end of Dimension 2 suggest a pattern of moderately-active auction fraud activities with the number of online fraud transactions (S2_11_30Tx), related earnings (S3_Earn1k_5k) and seizure value (S5_SeizureValue_10k_ 50k) falling in the middle of all the offender cases. Interestingly, this behavioral pattern clustered offenders who engaged in less than three months of online fraud (S1_Engaged3mLess).

- **Offender Type 2 (Intermediate-Inactive):** This cluster is marked with a "**o**" in Figure 2. Variables at the left end of Dimension 1 and the bottom end of Dimension 2 suggest a pattern of inactive auction fraud activities with the lowest number of transactions (S2_6_10Tx, S2_5TxBelow) and earnings per month (S3_Earn1kLess). In addition, these variables are also clustered with the lowest seizure value (S5_SeizureValue10kBelow) and the offenders who engaged in online fraud for a moderate period of time (S1_Engaged4_6m, S1_Engaged7_12m).

- **Offender Type 3 (Experienced-Active):** This cluster is marked with a "**-**" in Figure 2. Variables at the right end of Dimension 1 and the top end of Dimension 2 suggest a pattern of very active auction fraud activities with the largest number of transactions (S2_31_99Tx, S2_100TxAbove) and earnings per month (S3_Earn5kMore). In addition, these variables are also clustered with the highest seizure value (S5_SeizureValueAbove50k) and the offenders who engaged in online fraud for the longest period of time (S1_Engaged13mAbove).

The central region of the two-dimensional scaling plot (marked with three "**x**" symbols in Figure 2) shows an absence of variables related to online fraud offender behavior. Careful examination reveals that this common region shared by the three clusters is the source of goods bought, which means that all the offender types bought goods from similar sources. In addition, Dimension 1 suggests a measure of the activity level of offender behavior while Dimension 2 suggests a measure of the period of engagement in online fraud activities.

4.4 Discriminant Analysis Results

The k-means clustering technique (with $k = 3$ clusters) was used to group the offender cases. The data was analyzed using a non-parametric mean test with k-independent samples on the set of offender behavior variables. A Kruskal-Wallis test indicated significant effects of the grouping on engagement period ($\chi^2(2)$=17.189, p<0.01), transactions ($\chi^2(2)$=14.304, $p < 0.01$), earnings ($\chi^2(2)$=10.011, $p < 0.01$) and seizure value ($\chi^2(2)$=23.587, $p < 0.01$), but no significant effect on the source ($\chi^2(2)$=0.905, $p > 0.05$). These results are consistent with the results of the multidimensional scaling analysis described in the previous section, where the three types of offenders had distinct behavior, but no difference with regard to the sources of their auction items.

Further analysis indicated that the effects of the grouping on age ($\chi^2(2)$=7.08, $p < 0.05$), education level ($\chi^2(2)$=8.21, $p < 0.054$) and why not afraid of being caught ($\chi^2(2)$=10.22, $p < 0.01$) are significant. However, the effect on motive is marginally insignificant ($\chi^2(2)$=4.69, $p = 0.096$) and the effects on the other personal characteristics variables are not significant.

Upon closer examination of the three offenders types using the three significant personal characteristics variables, we noticed that the novice-moderately-active offender group is the youngest of the three groups (mean = 28), with half the offenders (50%) having tertiary or university or higher education levels (50%) and most of them (61.5%) believing that they would not get caught. On the other hand, the experienced-active offenders is the oldest group (mean = 36), with the vast majority of them (81.8%) having primary or secondary education levels and almost all of them (90.9%) claiming that they did not know that their activities were illegal. The mean age of the intermediate-inactive offender group is 29, most of them (79.2%) having a secondary school education level, about half of them (45.8%) claiming that they did not know that their activities were illegal and 41.7% believing that they would not get caught.

Discriminant function analysis was applied to differentiate the three offender types: novice-moderately-active, intermediate-inactive, and experienced-active. The independent variables corresponded to the personal characteristics, which included demographic characteristics (e.g., sex, age, education level and income level) and intrinsic motivation (e.g., objective and why the offenders were not afraid of being caught).

Table 3. Wilks' lambda and canonical correlations for the three offender types.

Function	Wilks' Lambda	χ^2	df	p	R_c	R_c^2
1–2	0.327	37.8	22	0.019	0.771	59.40%

Table 3 presents the Wilks' lambda and canonical correlations for the three offender types. The canonical discriminant functions show a high correlation (0.771) with an effect of $R_c^2 = 59.4\%$. The first and second functions significantly differentiate the three groups (Wilks' Lambda = 0.327, $\chi^2(22) = 37.8$, $p < 0.05$). The results obtained for the second function alone were not significant ($p = 0.713$).

Table 4. Standardized discriminant function and structure coefficients.

Scale	Coefficient	r_s	r_s^2
Function 1			
Sex (x_1)	–0.09	–0.20	3.96%
Age (x_2)	0.62	0.33	10.69%
Education Level (x_3)	–0.84	–0.28	8.07%
Occupation (x_4)	0.20	0.03	0.07%
Income Level (x_5)	–0.20	0.07	0.53%
Economic Status (x_6)	–0.04	0.04	0.14%
Marital Status (x_7)	–1.05	0.08	0.69%
Living Status (x_8)	0.52	0.18	3.13%
Arrest History (x_9)	–0.43	–0.21	4.20%
Objective (x_{10})	0.69	0.29	8.24%
Why no fear of being caught (x_{11})	0.75	0.35	12.11%

Table 4 presents the structure matrix and structure coefficients for the three offender types corresponding to the first function (Function 1). Note that age, education level and intrinsic motivation (objective and why [an offender was] not afraid of being caught) are primarily responsible for differentiating between the offender types. On the other hand, education level is negatively correlated with the other three variables, which are positively correlated in Function 1.

Table 5 shows the centroids of the three offender groups for Function 1. The group centroids suggest that intrinsic motivation and age (i.e., Function 1) tend to be most elevated for experienced-active offenders and least evident in novice-moderately-active offenders. This suggests that the offender type differences observed in Function 1 pertaining to the personal characteristics variables (age, education level, objective and

Table 5. Group centroids resulting from discriminant function analysis.

Offender Type	Function 1
Novice-moderately-active	–1.314
Intermediate-inactive	0.124
Experienced-active	1.761

why not afraid of being caught) can be attributed to experienced-active offenders.

Based on the data presented in Table 4, the following equation can be used to determine the offender type based on personal characteristics information:

$$\begin{aligned} \textit{Offender Type}\,(\textit{Function}\,1) \;=\; & -0.09x_1 + 0.62x_2 - 0.84x_3 + 0.20x_4 \\ & -0.20x_5 - 0.04x_6 - 1.05x_7 + 0.52x_8 \\ & -0.43x_9 + 0.69x_{10} + 0.75x_{11}. \end{aligned}$$

Tests of this equation with the available data revealed that 78.6% of the original cases were classified correctly.

5. Discussion

The results of the study show that a multivariate approach [6] is useful for profiling online auction offenders. Three distinct types of offenders, novice-moderately-active, intermediate-inactive and experienced-active, were identified using multidimensional scaling and hierarchical clustering, and these three types of offenders are statistically different.

Discriminant analysis applied to the personal characteristics variables yielded an equation (model) for offender type determination that is 78.6% accurate when used with the available data. In addition, certain personal characteristics variables (i.e., age, education level, objective and why not afraid of being caught) have higher predictive values in discriminating online auction fraud offenders. These variables are most elevated in the case of experienced-active offenders, which is consistent with the k-independent sample test results (i.e., a group of older offenders with lower education levels who mostly believed that the online auction activities they were conducting were not illegal). At the other end are the novice-moderately-active offenders, typically young with high education levels who did not believe that they would get caught, which is also consistent with the k-independent sample test results. Additionally, although the experienced-active offenders said that they were unaware

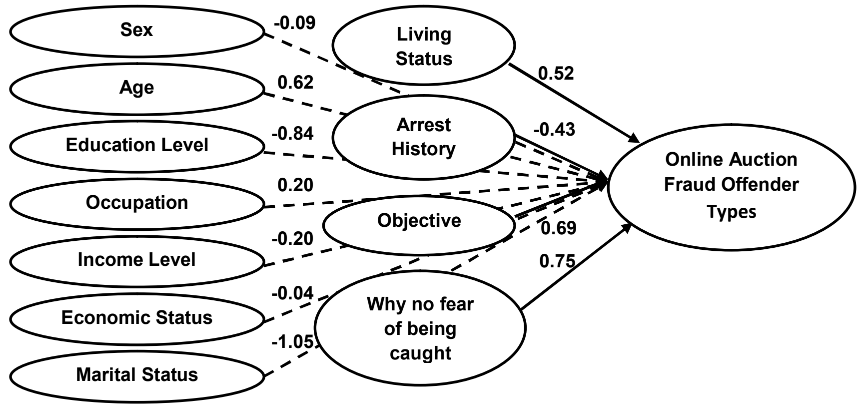

Figure 3. Predictive model of offender types based on Function 1.

that their online auction activities were illegal, there is the possibility that they were lying to law enforcement investigators.

Figure 3 shows the predictive model constructed based on the results of this study. This model could assist investigators in narrowing their search for offenders after the online auction activities and behavior of the subjects are known.

The two personal characteristics variables, objective and why not afraid of being caught, correspond to the intrinsic motivation of offenders. Interestingly, the results of the study reveal that this psychological factor may play an important role in predicting the offender type. As Rogers, *et al.* [13] note, like any other crime, people are also involved in cybercrimes, so it is necessary to include psychological traits and personal characteristics when profiling cyber criminals. Therefore, it would be useful if future research on online auction fraud (and other cybercrimes) could also study how psychological factors could be used to predict offender behavior.

The current study only considered online auction fraudsters who were apprehended. It is possible that undetected offenders may have certain personal characteristics that could enhance prediction. Although the inclusion of undetected offenders is difficult in empirical research, it is, nevertheless, important to acknowledge the fact that this group was not considered in the study.

In addition, the use of law enforcement records as research data is not ideal. The data was not collected for the purpose of empirical research and, therefore, may be biased towards criminal investigations [2]. In fact, Farrington and Lambert [5] note that law enforcement data has limited utility with regard to offender profiling.

The results of this exploratory study show how a taxonomy of online auction fraud offenders can be created and that certain personal characteristics could predict the offender type. A good topic for future research is to collect data pertaining to additional personal characteristics and examine if the profiling of online auction fraudsters could be improved. In particular, the motivations of offenders could be explored more deeply to discern new offender behaviors. Additionally, the multivariate profiling approach employed in this study could be applied to other types of cybercrimes.

6. Conclusions

Multivariate behavioral analysis is a promising approach for profiling online auction fraud offenders. Multidimensional scaling and hierarchical clustering of the various offender behavior variables yielded a taxonomy of three distinct types of auction fraud offenders: (i) novice-moderately-active; (ii) intermediate-inactive; and (iii) experienced-active. Personal characteristics were also found to be predictive of the offender types; discriminant analysis of the personal characteristics of offenders resulted in 78.6% accurate identification of the offender type.

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