

## A Methodology for Profiling Paraphilic Interest in CSEM Users on Peer-to-peer Networks

Margaret Brennan and Sean Hammond

School of Applied Psychology, University College Cork

## Author Note

Margaret Brennan, School of Applied Psychology, University  
College Cork, Ireland, E: [m.brennan@ucc.ie](mailto:m.brennan@ucc.ie) T: +353214904551;

Sean Hammond, School of Applied Psychology, University College  
Cork, Ireland, E: [s.hammond@ucc.ie](mailto:s.hammond@ucc.ie) T: ++353214904551

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Correspondence concerning this article should be addressed to Margaret Brennan, School of Applied Psychology, UCC Enterprise Centre, North Mall, Cork, Ireland. E: [m.brennan@ucc.ie](mailto:m.brennan@ucc.ie) T: +353214904551

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Abstract

This paper describes the development of a novel methodology for profiling paraphilic interest in the search behaviour of users of online “Peer-to-peer” networks - a major vector for the exchange of Child Sexual Exploitation Material. The profiling methodology focuses on problematic paraphilic interests, involving illegal or non-consensual activities associated with the sexual victimisation of children. This work extends an earlier typal analysis carried out by Hammond, Quayle, Kirakowski, O’Halloran and Wynne (2009) in which a distinct problematic paraphilic typology was uncovered in the search behaviours of Peer-to-peer users. The methodology described focuses on the subsequent development of a Latent Class Model that underpins the operation of the profiling application. The composite profiling process is described. Finally, we discuss the prospective applications of this profiling process and the implications of our methodological design. We identify a series of recommendations for future research and for the design of profiling and risk appraisal processes with application to online CSEM offending behaviour.

*Keywords:* Child Sexual Exploitation Material; Internet Investigation; Profiling; Paraphilia; Risk Assessment; Peer-to-peer; Latent Class Analysis

*Word Count: 6,235*

## 1    **Introduction**

2

## 3    ***Terminology***

4    Throughout this article, the authors use the term “Child Sexual Exploitation  
5    Material” (CSEM) in accordance with the definition and associated notation  
6    offered by Merdian (2012). We use the acronym “P2P” to denote to “Peer-  
7    to-peer” file sharing networks, the online forum for CSEM offending  
8    considered in this study.

9

## 10   ***The Role of P2P Networks in CSEM Offending***

11   Recent years have seen growing concerns about the role of online P2P  
12   facilities in the sexual exploitation of children, particularly in terms of their  
13   capacity to facilitate expedient, large-scale CSEM access (Choo, 2008;  
14   Hughes et al., 2006). Parallel concerns have been expressed around the  
15   incidence of children’s exposures to illicit and illegal sexual media in these  
16   environments (Dombroski, Gischlar & Durst, 2007; Greenfield, 2004;  
17   Quayle & Latapy, 2008). To a large extent, these concerns have their  
18   impetus in a small but established body of empirical evidence that points to  
19   increasing volumes of CSEM and attendant offending activity on P2P  
20   networks. While estimates of the extent of CSEM exchange on P2P  
21   networks vary considerably, it is now widely conceded that P2P serves as a  
22   major vector for the distribution of illegal CSEM (Hughes et al., 2008;

1 Taylor, Haggerty, Gresty & Fergus, 2010; US Department of Justice, 2010,  
2 Wolak, Liberatore & Levine, 2014).

3 International empirical evidence points to the problem of P2P-  
4 facilitated CSEM offending as endemic. A pioneering study by Hughes et  
5 al. (2006) found that 1.6% of searches and 2.4% of responses on the  
6 “Gnutella” P2P network related to illegal sexual content such as rape,  
7 bestiality and child abuse. Hughes et al. (2008) revisited this data to  
8 determine how much of this traffic was specifically CSEM-related and  
9 determined that approximately 1% of queries (searches) and 1.5% of query  
10 hits (returned filenames) were associated with this material. Given the  
11 system’s scale, and the fact that the study only covered a portion of the  
12 Gnutella network, the authors suggested that on the Gnutella network alone,  
13 hundreds of searches for CSEM occur each second. Similarly, in an analysis  
14 of a larger sample of Gnutella network traffic, Steel (2009) found that a  
15 significant proportion of these exchanges were CSEM-related. Here,  
16 approximately 1% of all observed queries and 1.45% of query hits on the  
17 network were CSEM-related. In a similar vein, substantial volumes of  
18 paedophilic queries have been observed on the “eDonkey” P2P network  
19 (Latapy, Magnien & Fournier, 2009). Here, the authors identified two  
20 keyword-based searches per thousand (0.2%) as CSEM-related with a  
21 similar proportion of eDonkey users engaging in such searches. With tens of  
22 P2P networks in use, the scale of CSEM-related activity on P2P can be  
23 estimated to be in the tens, if not hundreds of thousands of exchanges per  
24 day.

1           The decentralised, private nature of P2P file sharing, its open-access  
2 policies and rate of growth make its content extremely difficult to control  
3 and enable persons with deviant sexual interests to access and exchange  
4 CSEM on these networks with relative ease and anonymity (Nielssen et al.,  
5 2011; Westlake Bouchard & Frank, 2011). In networks such as eDonkey  
6 and Gnutella, there is no central server that can be traced and held  
7 accountable for shared illegal content, making dissemination of CSEM  
8 across the network almost impossible to prevent. These features of P2P  
9 networks naturally limit law enforcement capacity for intervention and have  
10 resulted in a situation where deviant sub-communities have flourished  
11 within these forums (Hughes et al., 2006; Steel, 2009).

12

### 13 ***Paraphilic Activity on P2P***

14 It has long since been suggested that individuals with distinct paraphilic  
15 interests use P2P networks to engage with CSEM and other problematic  
16 materials. For example, in their analysis the distribution of pornographic  
17 material on the Gnutella network, Mehta, Best and Poon (2002) monitored  
18 Gnutellameter, a website that captures data exchanged in Gnutella and  
19 generates summaries of keywords most commonly entered by its users. The  
20 authors identified pornographic imagery as one of the most commonly  
21 sought materials on the network with user searches displaying a strong  
22 emphasis on paedophile and hebephile content. Similarly, in the Steel  
23 (2009) study, the majority (76%) of those who engaged in age-specific  
24 searches for CSEM sought imagery featuring children between 11 and 16  
25 years of age, indicative of a prevailing hebephilic disposition in those

1 searching for CSEM on the network. Steel also observed significant  
2 correspondence between the use of bestiality and CSEM-related search  
3 terms in the search behaviours of P2P users - his analysis of CSEM-related  
4 queries established that the search term “Zoofila” was most commonly  
5 coincident with CSEM-related terms in relevant user queries on the  
6 network. Hammond et al. (2009) determined that the largest proportion of  
7 problematic paraphilic searches on the eDonkey network related to  
8 hebephilic content. Their typal analysis offered forcible evidence of discrete  
9 paraphilic sexual interests in P2P user search behaviours.

10

#### 11 ***P2P-facilitated CSEM Offending - Challenges to Law Enforcement***

12 The prevalence of paraphilic and CSEM-related activity on P2P systems has  
13 incited substantial responses from international law enforcement,  
14 witnessable in increasing arrest rates for P2P-facilitated CSEM offences and  
15 an intensification of investigative activity across these networks. For  
16 example, offenders who used P2P networks to access CSEM featured in 4%  
17 of US arrests for CSEM possession and distribution offences in 2000. By  
18 2009, P2P-accessed CSEM featured in 61% of all such arrests (Wolak,  
19 Finkelhor, & Mitchell, 2012). Similarly, there has been a significant  
20 concentration of investigative resources in the development of monitoring  
21 solutions such as “Child Protection System” that support the apprehension  
22 of CSEM offenders on P2P systems. Notwithstanding these developments,  
23 pervasive challenges remain in terms of the current scale of P2P-facilitated  
24 CSEM offending.

1           In their recent investigation of one year of CSEM exchange by US  
2 computers on the Gnutella network, Wolak, Liberatore and Levine (2014)  
3 illustrated the scale of this challenge to law enforcement, with hundreds of  
4 thousands of US computers implicated in P2P-facilitated CSEM exchange  
5 over the study period. In view of the scale of this offending activity, these  
6 authors highlighted the importance of adopting a more discriminating  
7 approach to the investigation of CSEM offences on P2P, whereby  
8 problematic P2P offenders are identified and prioritised by law enforcement  
9 for urgent intervention. More specifically, having identified that a very  
10 small proportion (less than 1%) of computers on the network made  
11 comparatively high yearly contributions of 100 or more files to the number  
12 of known CSEM files available on the system, these authors suggested that  
13 investigating law enforcement should use existing investigative software  
14 tools such as “RoundUp” or “ICAC Cops” to prioritise the users of these  
15 high-contribution computers for arrest and take their files offline, thereby  
16 substantially reducing the number of known CSEM files in circulation.

17           Liberatore, Erdely, Kerle, Levine and Shields (2010) observed that a  
18 primary goal of P2P investigations should be to apprehend child abusers and  
19 to help children that are being sexually victimised, rather than simply  
20 detecting and confiscating CSEM in the context of possession and  
21 distribution offences. These authors advocated the development of strategies  
22 to support the identification of those more likely to be directly involved in  
23 the sexual victimisation of children. Indeed, this objective is shared by  
24 investigating law enforcement internationally (Eke, Seto & Williams, 2011)  
25 and to date a small number of profiling strategies have been developed for

1 this purpose. For example, Long, Alison and McManus (2013) developed  
2 the Kent Internet Offender Risk Assessment Tool (KIRAT) which  
3 discriminates CSEM offenders at risk of contact offending on the basis of a  
4 range of factors, including the number and type of collected CSEM files and  
5 access to children.

6         However noble, this objective is particularly difficult to achieve in  
7 the investigation of abstract online exchanges on P2P, where little personal  
8 and behavioural information is available to profile prospective contact  
9 offenders. It is difficult for investigating law enforcement to infer offence  
10 motivation or outcome from the limited set of behaviours (e.g. file sharing  
11 and downloading) that may be observed on P2P. Indeed, Peersman, Rashid,  
12 Schulze, Brennan and Fisher (2014) reported that actualising reliable  
13 strategies for the identification of perpetrators of child sexual abuse during  
14 P2P investigations persists as a primary operational challenge for law  
15 enforcement. Furthermore, P2P offender identities are frequently unknown  
16 to online investigators, a situation that precludes the possibility of KIRAT-  
17 type assessment (where for example, information regarding the subject's  
18 access to children is required to inform the profile). Evidently, a strategy for  
19 profiling problematic CSEM offenders on P2P is required, which can  
20 accommodate the paucity of personal and behavioural data that is available  
21 for profiling purposes on P2P and respond to the reality of online  
22 investigations, where identity of the offender is often unknown.

23

24 ***The Psychological Profile***



1 All psychological profiles are, explicitly or implicitly, built around the  
2 notion of a taxonomy (Horgan, O’Sullivan & Hammond, 2003). Observed  
3 behaviours are then said to flow from the “type” of person we are dealing  
4 with. In the early years of offender profiling developments, the taxonomy  
5 utilised was derived from an a-priori theoretical model, often with some  
6 psychodynamic basis (Groth, Burgess & Holmstrom, 1977; Ressler,  
7 Burgess & Douglas, 1988). It quickly became apparent that systems that  
8 rigidly adhere to one or another psychological model are somewhat limited  
9 in scope and that a more behavioural approach was needed (Canter &  
10 Heritage, 1989). From this perspective profiles must be built upon large  
11 bodies of empirical data to generate the taxonomic models.

12 This led to a reliance on data analytic techniques whose primary  
13 advantage was that the taxonomies were based upon actual contextualised  
14 behaviour (Canter, Hughes & Kirby, 1998). Despite the greater ecological  
15 validity of these approaches, a major caveat remains. Data analytic  
16 procedures inevitably utilise large samples of offences and offenders to  
17 build the behavioural patterns that inform the profile. This entails a degree  
18 of aggregation across offenders and the best that can be achieved is a  
19 guesstimate of where a particular individual falls within the behavioural  
20 pattern. Unique individuals will always confound the profile to some  
21 extent. For this reason, this study has adopted a transparent model based  
22 upon a simple, empirically derived categorical taxonomy that provides a  
23 probability profile for each individual describing possible membership of  
24 each category.

1

## 2 ***Profiling P2P Behaviours***

3 Problematic P2P “types” are still largely unknown, although there is a likely  
4 continuity with general sexual offenders. This position assumes that the use  
5 of online P2P facilities is simply an extension of a person’s normal activities  
6 and interests. Thus, searching for and accessing CSEM on P2P networks  
7 simply reflects a person’s paedophilic predilections or other problematic  
8 paraphilic interests (Quayle, Hammond & Wynne, 2007). We know that  
9 such an assumption should not be automatic and the relationship that  
10 offenders have with technology is often more complex than this suggests  
11 (Calder, 2004; Carr, 2006; Quayle & Taylor, 2003). However, P2P user  
12 behaviours are difficult to operationalise for profiling or assessment  
13 purposes because there is only one source of interface accessible. With the  
14 paucity of behaviours available to us in online P2P systems, largely based  
15 around file searching and downloading behaviours, the assumption of  
16 behavioural continuity was necessary in the early stages of the development  
17 of the profiling methodology.

18 It should be borne in mind that P2P offences largely operate at a  
19 distance from the victim and are secondary in nature (Wolak, Liberatore &  
20 Levine, 2014), unless the offender generates CSEM shared on the network.  
21 Clearly, this does not mitigate the offense, but it does have psychological  
22 implications because it is not possible to assume that a P2P offender is  
23 automatically a contact offender. However, work with CSEM offenders  
24 does suggest that when paedophilic interest is the prime motive the risk of

1 contact offense is high (e.g. Quayle & Taylor, 2003; Sheldon & Howitt,  
2 2008). A considerable proportion of CSEM offenders are likely to be  
3 paedophilic or hebephilic and therefore present a direct risk to children  
4 (Eke, Seto & Williams, 2011; Seto, Cantor & Blanchard, 2006). In addition,  
5 exposure to CSEM and related materials may intensify interest through  
6 masturbatory conditioning and greater intensity of interest may drive a  
7 motive for contact offence (Sullivan, 2002). A further complication is that  
8 multiple paraphilias are common and it is likely that certain combinations  
9 are particularly high risk (Abel, Becker, Cunningham-Rathner, Mittelman &  
10 Rouleau, 1988). Thus, a paedophile with an interest in coercive and/or  
11 sadistic sex presents a dangerous combination (MacCulloch, Snowden,  
12 Wood & Mills, 1983). It is also important to note to that paraphilic sexual  
13 offenders frequently manifest concomitant impulse control problems (e.g.  
14 Dunsie et al., 2004) and are more likely to recidivate over time (Mann,  
15 Hanson & Thornton, 2010).

16 With this in mind, a typology with implications for risk may be  
17 reasonably built around the taxonomic notion of paraphilia (Abel &  
18 Osborne, 1992). A paraphilia is an abiding interest and, at the extreme, urge  
19 to engage in sexual activity of a deviant or problematic kind. Notable is the  
20 class known as paedophilia where the target of sexual interest is the  
21 prepubescent child. The fact that there may be subclasses of paedophilia  
22 that may have implications for risk, treatment and disposal is not explored  
23 here, although it may emerge as the use of the profiling methodology  
24 develops (see for example Greenberg, Bradford & Curry, 1995). Another  
25 important paraphilia in the context of child abuse is hebephilia. This is a

1 slightly contentious paraphilia where the target of interest is the pubescent  
2 or recently post-pubescent child (Blanchard et al., 2009). Legally, the  
3 distinction between hebephile and paedophile activity is minor as both  
4 involve sex with children; however, psychologically, there is a very strong  
5 distinction as there is some evidence to suggest that hebephiles, like fully  
6 functioning people, are triggered by secondary sexual characteristics, while  
7 paedophiles are not (Griffin, 2010; Hammond et al., 2009).

8         There are a huge number of paraphilias and most of them have no  
9 legal ramifications. However, Hammond et al. (2009) demonstrated that  
10 P2P behaviour based upon search terms used could be mapped onto a small  
11 subset of paraphilias which the authors termed “problematic paraphilias”,  
12 involving illegal or non-consensual activities associated with the sexual  
13 victimisation of children. This is the taxonomy that we wish to develop in  
14 order to establish the profiling methodology.

15

## 16 **The Present Study**

17 The primary aim of this study is to describe a profiling methodology for  
18 specific offender cases that may offer a basis for the categorisation of  
19 problematic profiles of sexual interest on P2P networks. The intended  
20 application of this profiling method is to the online investigation process,  
21 where generated profiles may be used to inform assessments of offence  
22 severity, candidate risk and related decisions to prioritise specific P2P cases  
23 for further investigation. The outcome of this study was designed to serve as  
24 a complementary, modular resource in the iCOP system (Peersman et al.,

1 2014) that was developed at Lancaster University under the aegis of the  
2 iCOP Project. Originally, this profiling methodology was envisaged as a  
3 post-apprehension aid that would be accessed once law enforcement  
4 agencies had identified a perpetrator. In this conception, background  
5 information on the offender would be entered into the system to provide a  
6 profile to aid disposal decisions, interview strategies, and other investigative  
7 decisions. However, in view of the above-identified needs of investigating  
8 law enforcement, it became apparent that a screening role for the profiling  
9 methodology was envisaged at a much earlier stage in the investigative  
10 process, during the online investigation phase.

11 In the following sections, we outline the development of the  
12 paraphilic profiling methodology. First, we describe the methodological  
13 considerations and premises that informed the development of the profiling  
14 process, as well as any associated limitations. We then present the  
15 background to the current study, describing earlier work undertaken by  
16 Quayle, Hammond and Wynne (2007) and Hammond et al. (2009) to  
17 empirically identify the “problematic paraphilic” categorisation upon which  
18 this profiling methodology is based. Next, we describe the development of  
19 the Latent Class Analysis Model, which underpins the psychological  
20 profiling methodology, and present a composite model of the profiling  
21 process. Finally, we discuss the prospective applications of this profiling  
22 process and the implications of our methodological design. We identify a  
23 series of recommendations for future research and for the design of profiling  
24 and risk appraisal processes with application to online CSEM offending  
25 behaviour.

1

## 2 ***Methodological Considerations***

3 Designing a profiling process with application at the online investigation  
4 stage presents some challenges in terms of methodological design because  
5 this screening role necessitates use of less informative data from an  
6 individual offender perspective. In many cases, the only behavioural data  
7 available at the online investigation stage is the P2P activity, which is  
8 largely limited to the use of search terms and the nature of the files being  
9 downloaded or shared. No demographics, criminal or psychiatric history  
10 information is available and this imposes severe limitations on the profiling  
11 methodology.

12 In order to accommodate this limitation it was decided that the  
13 profiling methodology should be built around a probabilistic model. It is  
14 vital to emphasise that the profiling process will not provide deterministic  
15 output, and in order to ascertain this we aimed to develop a model with a  
16 probabilistic output rather than a clearly defined, deterministic profile. The  
17 utility of such an approach may at first seem limited, but it is envisaged that  
18 this approach will provide more transparency to law enforcement decision  
19 makers and reduce the likelihood of false positive judgments in applied  
20 settings.

21 At the heart of the profiling methodology is the recognition that  
22 while empirical models are derived normatively, their application is nearly  
23 always idiothetic. This means that the best the generated profiles can be is  
24 suggestive. There is always a great concern when developing offender

1 profiles that the profile does not become reified. There are ample cases  
2 where profiles have so distorted investigations that cases have collapsed  
3 with great collateral damage all round (e.g. Wilson & Soothill, 1996).  
4 Therefore, we offer the profiling methodology as a *decision support tool* for  
5 law enforcement, with this caveat firmly to the fore. It is intended that the  
6 psychological profiles generated by this profiling method would be used as  
7 a complementary resource in investigative settings, and would be used as a  
8 supplementary point of information to inform case prioritisation and other  
9 relevant decisions.

10

#### 11 ***Premises of the Profiling Methodology***

12 There are three basic premises to our approach in developing the profiling  
13 methodology. Firstly, our psychological profiles should be based upon  
14 behaviours rather than assumptions. This means that the methods for  
15 obtaining the output profile are entirely transparent and are not based on  
16 individualised interpretation. It is true that the formulae used in the  
17 probabilistic model are based upon underlying statistical assumptions, but  
18 these are kept to a minimum by utilising a nominal level of analysis.

19 Secondly, the accessible P2P behaviours largely centre around the  
20 searches since it is with this volitional behaviour that the user betrays their  
21 interests and motives. Where search terms are not available it is possible to  
22 use the file sharing or downloading behaviour in terms of the nature of files  
23 being downloaded. However, in the context of this study, this strategy was  
24 considered problematic. Media files shared or downloaded on a P2P

1 network do not maintain that same volitional quality that characterises P2P  
2 search behavior. There are many possible reasons for this, for example, the  
3 filenames on downloaded media may have little relation to file content, or  
4 P2P users may download CSEM and other media in bulk on P2P networks,  
5 when the primary sexual interest may be in only one or two files in a large  
6 downloaded set. There are no other volitional features of P2P behaviour that  
7 can be reliably utilised for psychological profiling.

8 Finally, the model we apply is based upon a latent structure in which  
9 the latency is viewed as categorical. This enabled us to be consistent with  
10 the diagnostic model of paraphilia. Further research may expand this model  
11 by opening up multiple latencies or even allowing latent variables to be  
12 continuous. However, these extensions may require tighter assumptions  
13 that may only be justified by experience of the profiling methodology.

14

## 15 **The Profiling Methodology**

### 16 ***Background to the Study***

17 The development of the profiling methodology extended work carried out in  
18 an earlier European Commission funded study, the Measurement and  
19 Analysis of P2P Activity Against Paedophile Content (MAPAP) Project  
20 (e.g. Quayle, Hammond & Wynne, 2007).

21 Quayle, Hammond and Wynne (2007) carried out an analysis in  
22 which a list of 119,869 P2P search terms was trawled for words with a  
23 sexual connotation. An exhaustive search of the list was carried out to



1 identify terms that indicated sexually related material. To aid this process, a  
2 computer program was written in order to isolate words or part-words  
3 according to a given theme. The result was the identification of 25 specific  
4 themes or categories defined by their sexual and fetishistic content. Specific  
5 terms and words associated with each of the 25 categories of sexual interest  
6 were identified.

7

### 8 ***Identification of Individual Sexual Interest Profiles***

9 A computer program was then written to scan, in a serial fashion, over  
10 3,000,000 P2P submissions collected from the eDonkey facility in 2009.  
11 For each case, a record containing variables representing the 25 themes was  
12 created. Each variable was initially set to zero. If a sought after word  
13 occurred in the data set for that case, then the variable representing the  
14 theme in which it is placed was incremented by one.

15 If, after scanning, a case had no occurrence of the critical words it  
16 was jettisoned and the program moved onto the next case. If, on the other  
17 hand, the case did contain critical words, the record of 25 themes was  
18 retained. In this way the program identified 62,940 cases where a P2P user  
19 had made one or more sexually related submission. In each case the 25  
20 variables contained the frequency with which terms are submitted within  
21 each of the 25 thematic categories. In order to control for the fact that each  
22 theme is built of differing numbers of terms the data was represented in  
23 binary form thus:



1

2 This “problematic paraphilic” typology, identifiable in P2P search  
3 behaviours, formed the empirical basis of the subsequent Latent Class  
4 Modelling approach adopted by the authors in the development of the  
5 profiling process.

6

### 7 ***The Psychological Profiling Model***

8 Building upon these earlier findings it was necessary to fit a model that  
9 would be able to infer the positioning of individual cases. To this end, there  
10 are several modelling options available, ranging from deterministic models  
11 such as clustering through fuzzy set or latent trait modelling. On the basis  
12 of the premises noted above, a Latent Class model was selected (Lazarsfeld,  
13 1950; Magidson & Vermunt, 2004). This is a probabilistic approach as  
14 opposed to the more deterministic Configural Frequency Analysis. Latent  
15 Class modelling maintains an advantage over descriptive analytical  
16 approaches like Configural Frequency Analysis as it allows us to describe  
17 the probability of membership of multiple categories (problematic  
18 paraphilias) for given individual. A further advantage of the Latent Class  
19 modelling approach is that it enables meaningful summarisation of very  
20 large behavioural datasets, such as that which was utilised in this study.

21 For simplicity’s sake, the particular form of the model is one with  
22 one latent variable (Paraphilia) made up of 7-categories.

1 Latent Class Modelling may be defined in the following formula  
2 where, for brevity, 4 indicators (A, B, C and D) are shown.

$$\pi_{ijklt} = \pi_t^X \pi_{it}^{A|X} \pi_{jt}^{B|X} \pi_{kt}^{C|X} \pi_{lt}^{D|X}$$

3

4 Where  $\pi_t^X$  is the probability of being in class t on latent variable X  
5 while  $\pi_{it}^{A|X}$  is the conditional probability of i<sup>th</sup> response on indicator A when  
6 a member of class t and  $\pi_{ijklt}$  is the probability of someone presenting with  
7 the profile ijkl in latent class t.

8 Latent Class Modelling requires customised software although  
9 modules may be accessed via systems such as R. The most direct way of  
10 fitting the model and deriving the conditional probability parameters is to  
11 use an iterative approach beginning with rough model estimates in order to  
12 generate maximum likelihood estimates (Goodman, 1974). However, there  
13 is no guarantee of reaching a local function minimisation so it is advisable  
14 to carry out the analysis a number of times using different starting points.  
15 This means that the analysis may be time consuming. However, such an  
16 analysis is not required for each profiling session as in order to generate the  
17 profile the most recent parameters are used in a relatively simple form. To  
18 classify individuals, a probability of class membership to each of the t  
19 classes is identified based upon the behaviour profile thus:-

20

$$p_t = \frac{\pi_{ijklt}}{\sum_t \pi_{ijklt}}$$

1

2           The modal  $p_t$  indicates the most salient class or paraphilia for that  
3 person. The relative nature of the classification allows for complex  
4 membership profiles such that individuals with multiple paraphilias may be  
5 observed.

6           A set of routines written by the authors for a Windows platform  
7 (Pascal Code) was used to perform the Latent Class Analysis and the  
8 subsequent classification.

9           The data (comprising 62,940 cases, as described above) was fitted to  
10 a number of unrestricted latent class models ranging from 2 to 8 underlying  
11 classes.

12

## 13   **Results**

14   The 7-class model, fitted to the data from 62,940 cases, was found to be the  
15 best fitting using the log-likelihood statistic and the Bayesian Information  
16 Criterion (BIC). The log likelihood emerged at 59.12 with 107 degrees of  
17 freedom and the BIC at 93.90. The Disimilarity Index for this model was  
18 0.004, showing an excellent fit of the model and the data. The conditional  
19 probabilities are presented in Table 1. The existence of a set of relatively  
20 “pure” types corresponding with each of the 7 paraphilias is evident.

Themes	Classes						
	1	2	3	4	5	6	7
Gerontophilic	0.000	0.998	0.000	0.000	0.000	0.000	0.000
Bestiality	0.008	0.028	0.026	0.000	1.000	0.019	0.054
Paedophilic	0.000	0.000	0.001	0.000	0.046	0.004	1.000
Hebephilic	0.000	0.035	0.008	1.000	0.010	0.020	0.003
Sadistic	0.000	0.031	0.001	0.000	0.000	1.000	0.000
Rape	0.000	0.000	1.000	0.001	0.000	0.000	0.001
Incest	0.997	0.000	0.000	0.000	0.000	0.000	0.000
Class Probabilities	0.019	0.072	0.143	0.279	0.230	0.101	0.154
Diagnostic Statistics							
Log Likelihood	59.12						
2LL	118.23						
Pearson $\chi^2$	194.60						
Pearson $\chi^2$ under independence	8281.38						
Dissimilarity Index	0.004						
BIC	93.90						

**Table 1. Latent Class Analysis of Paraphilic Themes: The 7-Class Solution**

1

2

### 3 Discussion

#### 4 *Application of the Latent Class Model: P2P Investigation*

5 State of the art P2P investigation systems maintain a range of tools that  
6 allow investigators to prioritise persons of interest based on the number or  
7 the type of CSEM files they engage on these networks. However, the  
8 available literature suggests that a persistent challenge is to develop a  
9 solution that discriminates those who may present enhanced risk for contact  
10 sexual offending and recidivism, such as those presenting with profiles of  
11 problematic paraphilic interest. Given that no personal information about  
12 CSEM users themselves is gathered by existing monitoring systems (Wolak  
13 et al., 2014), this requirement is not currently supported, as no personal

1 information is accessible to investigators that could readily support such  
2 decisions.

3       Therefore, the authors have designed the methodology to be  
4 implemented as a complementary, elective function that would be integrated  
5 into existing monitoring systems. In its current conception, this function  
6 may be invoked at the discretion of the investigator to support their  
7 decisions to prioritise detected CSEM offenders for investigation based on a  
8 psychological profile of their problematic paraphilic interest. For example,  
9 where resources are limited, the paraphilic profiling function may be  
10 invoked to help investigators to discriminate amongst individuals with  
11 comparatively high contributions of CSEM files to P2P systems, such that  
12 priority cases may be identified for further investigation and prosecution.

13       Importantly, this profiling methodology supports an initial  
14 psychological profiling of cases where no background information on the  
15 individual is known, providing psychological indicators that are not  
16 available in other systems at pre-arrest level. While comparatively simple  
17 strategies such as paraphilic keyword or high intensity search detection may  
18 be feasible, the latent class model and associated profiling system provides  
19 the possibility to identify paraphilic profiles in a more sophisticated fashion.  
20 The presented methodology organises search-related information in a way  
21 that flags up potentially high-risk combinations of paraphilic interest and  
22 provides the user with a probabilistic profile, comprising a series of indices  
23 denoting that individual's likelihood of membership of each problematic  
24 paraphilic category. These features enable investigators to make more

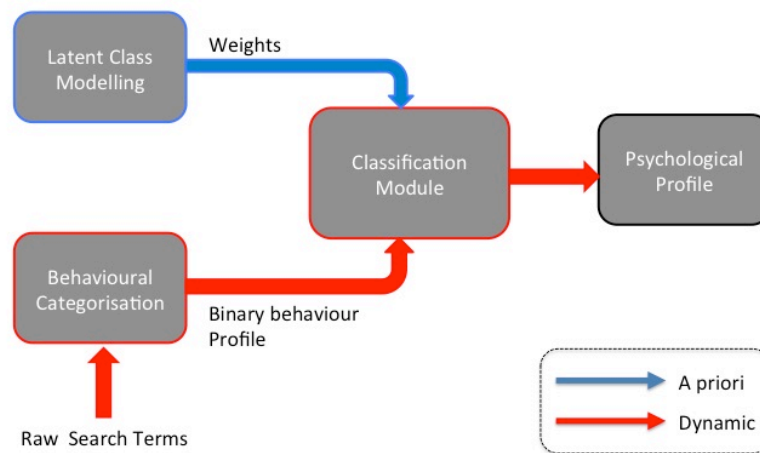
1 discriminating judgements to between CSEM users on P2P for prioritisation  
2 purposes. Moreover, the profiling methodology described here does not  
3 assume the presence of particular paraphilic types in P2P systems in a way  
4 that could increase the likelihood of false positive judgements, or otherwise  
5 misinform investigative decisions to prioritise certain cases. Rather the  
6 methodology relies on a series of empirically identified problematic  
7 paraphilic categories, discriminated in the preceding typal analysis of  
8 paraphilic interest on P2P (Hammond et al., 2009).

9

#### 10 ***The Composite Profiling Methodology***

11 The composite profiling methodology is illustrated at Figure 1, below. In  
12 the context of the profiling methodology, the Latent Class Analysis operates  
13 as a separate and static module and is not run every time there is a query on  
14 the profiling process. Rather, it is run once to generate the model  
15 parameters that are then stored. The classification module simply draws  
16 down the predefined parameters to produce the paraphilia profile, as  
17 illustrated (in blue) in the following process:





**Figure 1. The Composite Profiling Methodology**

The Behavioural Categorisation process indicated in Figure 1 is based upon Quayle, Hammond and Wynne’s (2007) a-priori thematic analysis carried out for the MAPAP Project described above. Where search terms input for a given individual, this categorisation process involves a simple “look-up” process in order to generate the binary indicators required for profiling. It should be noted that the words and search terms utilised by this behavioural categorisation process may need to be updated and extended in accordance with the emergence of new domain terminology, as it is identified by future law enforcement and related initiatives in the online child protection domain.

The binary indicator profile is passed to the classification process where the probabilistic profile is generated using formula 2 (above). In the end user scenario as currently envisaged, this output is relayed to the law

1 enforcement user for interpretation. A potential form of the output relayed  
2 to the end user is demonstrated in the relative profile illustrated at Figure 2,  
3 below.

4

P	H	G	S	C	I	Z
0.194	0.055	0.305	0.037	0.287	0.009	0.111
<i>(Gerontophile with coercive interests)</i>						
P = Paedophilic; H = Hebephilic; G = Gerontophilic; S = Sadist; C = Coercive; I = Incest; Z = Zoophilic						

5

6 **Figure 2. Sample Profile Generated by the Profiling Process**

7

8 No natural language formulation of this profile has yet been  
9 constructed because of the caveats mentioned above about reification of  
10 profiles. It is more important that detailed training is provided on the  
11 interpretation of these profile outputs, to reinforce the practical importance  
12 of using these profiles as a means of decision support rather than “decision  
13 making.”

14

## 15 ***General Discussion***

16 The profiling methodology developed at this study demonstrates a clear  
17 paraphilic typology in the search behaviours of P2P users that may maintain  
18 some salience in assessing and managing this population. The primary  
19 intended application of this profiling method is to online investigation  
20 processes, where generated profiles may be used to inform assessments of

1 offence severity, candidate risk and related decisions to prioritise specific  
2 P2P cases for further investigation. Evidently, these profiles may have a  
3 secondary application in investigative settings in the sense that they may  
4 inform assessments of seized CSEM, or help to determine the nature or  
5 sequence of topics that could be explored in suspect interviewing strategies.

6         It should be borne in mind that the results presented above come  
7 from the use of P2P search behaviour (search terms and submissions). The  
8 utility of the profiling system is contingent upon access to forms of  
9 behavioural data that are volitional, and that allow us to meaningfully  
10 identify paraphilic profiles (or other indicators of sexual risk) in P2P  
11 contexts. Arguably, all psychological profiling should be based upon  
12 volitional behaviours. Examining search terms appears to allow us to profile  
13 in this way, however other behavioural features of P2P use (e.g.  
14 downloading and sharing behaviours) do not appear to maintain that same,  
15 volitional quality that characterises P2P search behavior and may not hold  
16 same value for profiling purposes. State of the art investigative monitoring  
17 systems for P2P such as iCOP (Peersman et al., 2014) and Child Protection  
18 System tend to prioritise shared or downloaded files as the principal unit of  
19 analysis. From a policing perspective, an approach that prioritises file  
20 content is perfectly justifiable as it offers direct avenues to victim  
21 identification and the identification of sexual victimisation. However, for  
22 the purposes of a psychological profile search behaviours may be preferred,  
23 in view of their highly volitional character.

1           The model developed for the purposes of the profiling methodology  
2 shows good promise in terms of its content validity. However, further work  
3 is required to establish the predictive validity of the profiling system using  
4 live search data on P2P systems; to further determine the salience of the  
5 paraphilic profiles developed with this methodology to investigative and  
6 disposal decisions. This suggests a requirement for an end-user supported  
7 trial in live P2P investigation settings. Such a trial would establish apposite  
8 mechanisms for positioning and integrating the profiling methodology with  
9 investigative workflows and processes, and help identify what policies and  
10 training needs are required to support its deployment in live investigative  
11 settings.

12           The psychological profiles of paraphilic interest generated by this  
13 methodology may also maintain some value when applied to more  
14 traditional, clinical-forensic risk assessment processes. Notwithstanding the  
15 substantive mediating influence of the online environment in the  
16 commission of child sexual offences within P2P and other online forums, as  
17 well as the salience of contextual “crime scene” information that may be  
18 drawn from these environments to forensic risk assessment processes (e.g.  
19 West & Greenall, 2011), it is common that clinical-forensic professionals do  
20 not have access to such data when formulating assessments of online child  
21 sexual offenders. This situation is largely attributable to the illegal character  
22 of CSEM and the inaccessibility of materials and online forums implicated  
23 these offences to non-law enforcement professionals. As aforementioned,  
24 this situation can be problematic given the apparent salience of this  
25 information to the formulation of comprehensive risk assessments, disposal

1 and other management decisions. Therefore, the paraphilic profile generated  
2 by the law enforcement user may serve as a useful, supplementary point of  
3 information for the clinical-forensic practitioner regarding the character of  
4 the P2P offender's sexual deviance; such information may not otherwise be  
5 accessible for assessment purposes. Furthermore, the profiling methodology  
6 delivers this information in a way that does not require the assessor to  
7 directly engage with CSEM and related online behaviours and  
8 environments. This feature of the process may also be beneficial given the  
9 distressing and potentially corrosive nature of exposures to CSEM and  
10 related offending practices (e.g. Powell, Cassematis, Benson, Smallbone &  
11 Wortley, 2014).

12 A further, final advantage of the profiling methodology presented in  
13 this study is that it is sensitive to the situational factors that impact upon the  
14 commission of CSEM offences on P2P. In the field of offender profiling, a  
15 broad range of studies have demonstrated the variability of offending  
16 behaviour in response to contextual and situational factors; particularly in  
17 relation to sexual offences (Alison, Goodwill, Almond, van den Heuvel &  
18 Winter, 2010). Moreover, sexual offences committed through P2P systems  
19 are almost entirely mediated by the online environment; in this way the  
20 enactment of the offence behaviour and offending outcome may be shaped  
21 by the functionalities the online interface, and other dynamic contextual  
22 factors. Notwithstanding the formative influence of online offending  
23 contexts on criminal outcomes, current systems offered for the purposes of  
24 investigative risk appraisal and case prioritisation (of which there are very  
25 few) do not appear to attend to the mediating role of these contextual

1 influences on offending behavior. Specifically, these systems do not appear  
2 to account for the possibility that extraneous features of the online  
3 environment may enable or constrain the expression of volitional  
4 components of offence-related behaviours, so colouring attendant  
5 conclusions that may be drawn about the nature of the individual's sexual  
6 interest or prospective risk. As we have seen in the context of P2P, these  
7 specific contextual influences may substantially compromise the volitional  
8 character of certain P2P behaviours (e.g. number/type of filenames  
9 downloaded), and, by extension, their utility for risk assessment purposes.

10 To conclude, this study demonstrates a clear speciation of  
11 pornographic interest, identifiable in the searching behaviours of P2P users.  
12 As mentioned above, future analyses to refine the model may reveal other  
13 relevant distinctions or sub-classifications in profiles of paraphilic search  
14 behaviour, e.g. preferences for boys vs. girls; for specific age groups and  
15 developmental stages, etc. Successful demonstration of such subclasses of  
16 search behaviour and paraphilic interest may hold significance for risk  
17 assessment purposes. For example, it has been well established that sexual  
18 offenders who maintain preferences for male children are more resistant to  
19 treatment and tend to recidivate at a higher rate (e.g. Hanson & Bussiere,  
20 1998; Harris & Hanson, 2004; Petrunik & Deustchmann, 2008); much as  
21 those who sexually offend against both girls and boys maintain a  
22 particularly high risk of sexual recidivism (e.g. Langevin et al., 2004). The  
23 suggested salience of such sub-classifications to the identification of  
24 recidivistic and contact offending potential in CSEM offenders is perhaps  
25 all the more pertinent in light of the findings of a recent study of recidivism

1 predictors in a Canadian sample of “child pornography offenders” (Seto &  
2 Eke, 2015), which suggests that those whose CSEM collections indicate  
3 paedophilic or hebephilic preference for male children are more likely to  
4 reoffend across CSEM and contact sexual offence types.

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