Judging the algorithm: A CASE STUDY ON THE RISK ASSESSMENT TOOL FOR GENDER-BASED VIOLENCE IMPLEMENTED IN THE BASQUE COUNTRY

Ana Valdivia  
King’s College London (KCL)  
London, United Kingdom  
amana.valdivia@kcl.ac.uk

Cari Hyde-Vaamonde  
King’s College London (KCL)  
London, United Kingdom  
cari.hyde-vaamonde@kcl.ac.uk

Julián García Marcos  
Euskal Herriko Unibertsitatea (EHU)  
Bizkaia, Spain  
jgarcia421@ikasle.ehu.eus

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ABSTRACT

Since 2010, the output of a risk assessment tool that predicts how likely an individual is to commit severe violence against their partner has been integrated within the Basque country courtrooms. The EPV-R, the tool developed to assist police officers during the assessment of gender-based violence cases, was also incorporated to assist the decision-making of judges. With insufficient training, judges are exposed to an algorithmic output that influences the human decision of adopting measures in cases of gender-based violence.

In this paper, we examine the risks, harms and limits of algorithmic governance within the context of gender-based violence. Through the lens of an Spanish judge exposed to this tool, we analyse how the EPV-R is impacting on the justice system. Moving beyond the risks of unfair and biased algorithmic outputs, we examine legal, social and technical pitfalls such as opaque implementation, efficiency’s paradox and feedback loop, that could lead to unintended consequences on women who suffer gender-based violence. Our interdisciplinary framework highlights the importance of understanding the impact and influence of risk assessment tools within judicial decision-making and increase awareness about its implementation in this context.

1 Introduction

In 2018, M reported her ex-husband to the police authorities in the Basque Country (Spain). She suffered gender-based violence. During the report, the police authority asked her several questions and together with other evidence gathered through an investigation of the case, they fed the answers into a risk assessment tool. ‘Is the male aggressor or victim an immigrant?’, ‘Very intense jealousy or controlling behaviours?’, ‘Victim’s perception of danger of death in the past month’ (see Appendix A) are some examples of the items evaluated by this tool to ‘empirically establish risk markers of severe injuries and homicide in intimate partner violence’ [Echeburúa et al. (2009)] (see Figure 5). In the case of M, the algorithmic output assessed that her husband had a low-risk of further gender-based violence. The report of the M’s case together with the algorithmic evaluation was sent to the courtroom. After reading the report, but ultimately disregarding the algorithmic output, the judge assessed that M was in high-risk. Human experience, or in other words, the judge’s experience, led to questioning the algorithm. Although in M’s case there were no death threats assessed by the police, nor did the woman herself have a perceived risk of death, the perpetrator was stalking her and her daughter, which impacted negatively on their mental health. In this case, the perpetrator was not using an explicit violent behaviour, rather he stalked them by walking around their house or buzzing the entryphone of their apartment. Even though he had previous complaints due to gender violence and even a restraining order, the algorithm assessed him as low-risk. However, on this occasion the judge decided to ignore the algorithmic evidence by assessing M’s case as high risk and proposed another restraining order.

Algorithms have been introduced in police stations and courtrooms to facilitate the decision-making process of law enforcement actors. There is an increasing number of algorithmic-based solutions adopted by law enforcement
We propose an interdisciplinary framework to analyse the EPV and EPV-R from a technical and legal perspective. Which involve ‘predicting an individual’s behavior on the basis of how others have acted in similar situations (actuarial)’ women who suffered gender-based violence. (2017a); Angwin et al. The use of algorithms such as risk assessment tools to predict violence has a long-standing history. Statistical predictions through the lens of a user, which in this case is a judge of the Basque country, we analyse the human-algorithm interaction in the gender-based violence context. We start by outlining how risk assessment tools have transformed the evaluation of intimate partner violence to predict future violent behaviours of the perpetrator and revictimization [Campbell](1995). We describe different data-driven tools that have been deployed in the different countries within the US and the EU. Then, we focus the analysis on the EPV-R given the little attention it has brought in the critical human-computer interaction literature. Then, we move to examine the design process and the performance evaluation of this tool. Through this analysis, we identify risk, harms and limitations involved in using risk assessment tools for gender-based violence such as: opaque implementation, efficiency’s paradox and feedback loop. We claim that these tools could have serious consequences in the evaluation of violence and suggest considering data feminism and design justice [D’Ignazio and Klein](2020), Costanza-Chock (2020) principles within the context of algorithmic governance in gender-based violence.

2 Background

The use of algorithms such as risk assessment tools to predict violence has a long-standing history. Statistical predictions which involve ‘predicting an individual’s behavior on the basis of how others have acted in similar situations (actuarial)’ or on an individual’s similarity to members of violent groups’ [Campbell](1995) p.26 began in the eighties through the analysis of risk factors [Gottfredson and Gottfredson](1988); Miller and Morris (1988). Gottfredson and Gottfredson contend that violence can and should be predicted. To do so, they proposed several statistical strategies such as bootstrapping and contingency tables to overtake human judgments and do it better in the justice and mental health system, performing ‘more efficiently and more effectively’ [Gottfredson and Gottfredson](1988) p.318. Moreover, they justify the use of statistical tools by acknowledging that scholars such as Takeuchi et al. advise that human judgements are highly fallible. They argue these tools are generally better than humans. Yet statistics do not always outperform human judgements [Dressel and Farid](2018). The use of these tools implies some limitations that have been recently the focus of the field of fairness in machine learning and critical data studies. Some of these limitations are related with: the demystification of the neutrality and objectivity of algorithmic and statistical tools [Birhane et al.](2021); [Birhane and Grayson](2018), the unintended discrimination and disparate impact of these tools due to statistical bias [Chouldechova](2017a); [Angwin et al.](2016) and the influence that automated tools have on human decisions [Green and Chen](2019).

In 2004, Campbell designed a danger assessment instrument [See: https://www.dangerassessment.org/](Last accessed, February 16, 2022). 

1By its initials in Spanish: Escala de Predicción de riesgo de Violencia grave contra la pareja.

2Domestic, or intimate partner violence occurs irrespective of the gender of the individuals involved. Not all aggressors are male and not all victims are female. In this article we analyse the impact of EPV and EPV-R, which focus specifically on intimate partner violence, but this is an unhelpful reduction of the overall picture.

3See: https://www.dangerassessment.org/(Last accessed, February 16, 2022).
of each response for each item, predicts the danger of gender homicide. This danger assessment instrument is considered the pioneer in the context of gender-based violence, yet its approach can be considered a basic statistical prediction tool. However, through the development of machine learning techniques, these tools have evolved and become more sophisticated. Rodríguez-Rodríguez et al. compared different machine learning classifiers (logistic regressions, random forest, support vector machines and Gaussian process) to estimate the number of gender-based violence complaints. Using a different approach, Cumbicus-Pineda et al. proposed data mining techniques to better understand the causes of gender-based violence. Moreover, we observe that these algorithmic-based solutions to assess risk of violence are widespread in different regions of the world: Ecuador Cumbicus-Pineda et al. (2021), South Africa Amusa et al. (2020), India Dehingia et al. (2022).

Different EU Member States have adopted risk assessment and management approaches of intimate partner violence European Institute for Gender Equality (2019). These tools are widely used by different actors such as police, prosecutors, courts, social workers and health professionals European Institute for Gender Equality (2019) pp. 21. Moreover, some tools used in the EU are imported from other regions which could negatively impact on the tool’s performance given that gender-based or intimate partner violence depends strongly on the context. Yet most of the tools implemented in EU Member States are developed taking into account the national context. In Spain, the Sistema de Seguimiento Integral en los casos de Violencia de Género (VioGen) Pueyo et al. (2008), López-Ossorio et al. (2016) is the most well-known tool for assessing the risk of intimate partner violence. VioGen was designed adopting the Spouse Abuse Risk Assessment (SARA) developed in 2015 by Kropp et al. VioGen is implemented across the Spanish territory and has been reviewed and assessed several times to improve its performance. However, other risk assessment tools for intimate partner violence, also implemented in Spain, have drawn less attention. This is the case of the EPV-R Echeburúa et al. (2009, 2010), the tool used by the Basque police (Ertzaintza), has also been implemented within the Basque courthouses to assist judges in the decision-making (see Figure 1).

Overall, the main purpose of these tools is to reduce harm to female victims of intimate partner violence and their children and facilitate the gathering of detailed and relevant information about the victim and the perpetrator in intimate partner violence cases European Institute for Gender Equality (2019) p. 19. However, there is a lack of evaluation and accountability of these tools after their implementation in courtrooms to better understand to which extent the harm is reduced and the tool is able to accurately predict violence. One of the limitations identified across the literature is the fact that ‘[t]here is a relatively small body of empirical evidence to evaluate tools that assess the risk of intimate partner violence’ European Institute for Gender Equality (2019) p. 32. In fact, some of the studies assessing these tools have found that they have a weak to moderate predictive accuracy Nicholls et al. (2013). As Green and Chen claim we have limited understanding of their properties: most notably, whether and how they actually improve decision-making Green and Chen (2019) p.97.

3 The Intimate Partner Femicide and Severe Violence Assessment Tool (EPV and EPV-R)

The EPV aimed at predicting the risk of gender-based violence recidivism in the Basque Country and was applied to reported perpetrators within this region. The EPV was reviewed (EPV-R) and implemented in 2008 to provide non-clinical professionals (forensic psychologists, judges, police authorities and social workers) with the prediction that allows the adoption of protection measures for victims, after being reported to police authorities, appropriate to their specific needs and based on empirical criteria Echeburúa et al. (2010) p. 2. Since then, this risk assessment tool has been used in Basque courtrooms where judges decide how much protection a victim of gender-based needs influenced by the algorithmic output (see Figure 1).

3.1 The design process of the risk assessment tool for gender-based violence

This risk assessment tool is based on 20 items evaluating several aspects of aggressors and victims to classify the risks of gender-based violence recidivism. These items are grouped into five psychometric categories: (1) personal data, (2) relationship, (3) type of violence, (4) profile of the perpetrator, and (5) vulnerability of the victim (see Appendix A). It was developed by a research team made of clinical psychologists who used their expertise to propose a brief, easy-to-use scale tool that is practical for use by the police, social workers, forensic psychologists, and judges in their decision-making process Echeburúa et al. (2008) p.1055. This tool was also inspired by SARA Kropp et al. (2005), taking into account the local context Pueyo et al. (2008).

During the design process of this tool, records of 1,081 cases of male individuals who were reported by their partners or ex-partners were gathered between October 2005 and August 2006 Echeburúa et al. (2009). The cases were classified

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4 There is a relevant difference between gender-based violence and intimate partner violence. In this paper, we will analyse a tool focused on intimate partner violence cases which is considered a sub-type of gender-based violence.
1. Women report gender-violence to the police. The police analyzes the case and assesses the risk of violence using the EPV-R’s algorithm which consists of 20 psychometric items.

2. The police writes a report of the case with the outcome of the EPV-R assessing the risk of violence and (3) the judge decides which protection measures should apply.

Figure 1: How is the EPV-R implemented in the Basque courtrooms? (1) the police assesses the risk of gender-based violence recidivism using the EPV-R’s algorithm, (2) the police writes a report of the case with the outcome of the EPV-R assessing the risk of violence and (3) the judge decides which protection measures should apply.

Figure 2: Cutoff between sensitivity or TPR (purple) and specificity or TNR (orange) for each score of the EPV tool. Accuracy (bars) is higher when specificity is also higher given that the dataset is unbalanced (269 severe violence cases (positives) vs. 812 non-severe cases (negatives)). Source: Echeburúa et al. (2009).

into severe (24.88%) and non-severe violence (75.12%). To filter the most relevant items that present greater capacity to distinguish between cases, aggressors and their partners were interviewed by police officers with a questionnaire of 58 items. Then, a comparative analysis was run to filter and select only 20 items that constituted the EPV.

The comparative analysis relies on the results obtained in well-known statistical hypothesis test such as: Student’s t-test ($t$) and chi-squared’s test ($\chi^2$). $T$-test was applied to analyse statistically significant differences in the mean of scores between severe and non-severe aggressors, respectively. On the other hand, $\chi^2$-test was applied to study whether there exist statistically significant differences between the frequency distribution of groups. The reliability of the tool was assessed by calculating the Cronbach’s alpha which analyses the internal consistency of the 20 items.
3.2 Assessing the performance: How well does the tool classify the risk of gender-based violence?

The efficacy of the risk assessment tool was assessed by analysing the trade-off between sensitivity (true positive rate (TPR)) and specificity (true negative rate (TNR)). They evaluated the performance of the classification task by analysing the diagnostic efficacy (accuracy) of the tool setting different cutoff scores to distinguish between severe and non-severe violence. Figure 2 shows the percentage of sensitivity and specificity for every cutoff score obtained by the risk assessment tool. As expected, the rate of true positives (TP) is higher with low cutoff scores whilst the rate of true negative (TN) is higher with high cutoff scores. However, the rate of false positives (FP) is higher than the true positives:

Thus, for example, a total score of 10, considered high risk, includes 48% of the severe aggressors, which means that one half obtain lower scores, and only 18% of the less severe aggressors obtain this score (false positive). If a stricter cutoff score had been chosen (e.g., 12), this would comprise 29% of the severe cases, and there would be a much lower number of false positive (6%), but at the cost of leaving out many severe aggressors (71%; false negatives). In contrast, if a lower cutoff score had been chosen (8 or 9), it would include not only a higher number of severe aggressors but also a large number of non-severe cases (false positives), which would limit the predictive capacity of the instrument. (Echeburúa et al., 2009, p. 932)

Then, a cutoff of 10 was proposed to discriminate between severe and non-severe cases:

The proposed cutoff scores represent a reasonable equilibrium between the need to adequately detect the severe aggressors and the suitability of not extending this label to an unnecessarily high number of men who have behave violently against their partner, and those who, event though they committed an offense present a moderate or a low risk of carrying out severe behaviours that can place their partner’s life at risk. (Echeburúa et al., 2009, p. 933).

In the context of gender-based violence, FP and FN do not play the same role which implies that ‘reasonable equilibrium’ between both error rates might not be desirable. A FP means that a case has been wrongly classified as severe when it was actually non-severe. On the other hand, FN means that a case has been wrongly classified as non-severe when it was actually severe. Thus, FN could imply that the gender-based violence case is underestimated which could imply putting women’s life and that of their relatives at a serious risk. It is then preferable to obtain higher rates of FP than FN, which implies that in the worst case scenario, cases with a non-severe risk of violence are categorised as high risk, implying perhaps greater attention. However, as observed in Table 1 the number of FN is higher than TP when the
In gender-based violence scenarios, risk assessment tools should obtain better performance metrics, obtaining higher percentage of sensitivity which implies that severe cases are correctly identified. Source: Echeburúa et al. (2010).

cutoff score is 10. This means that the assessment tool is more likely to classify severe cases as non-severe at this score, which could imply the underestimation of cases. Finally, reporting accuracy or AUC (see Figure 3) to assess the efficacy in unbalanced datasets as in this case (269 severe vs. 812 non-severe) could be dangerously misleading, leading to the accuracy paradox. In other words, if the dataset is unbalanced and the algorithm classifies better instances in the majority class (non-severe) rather than instances in the minority class (severe), accuracy obtains high scores which could lead to the wrong conclusion that algorithm’s performance is good. In fact, the accuracy reported at 10 is 73.1% (see Figure 2), yet the difference between TP and TN rates is high: 47.96% and 81.40% respectively. In this case, it is preferable to reduce high FN rates and report metrics such as precision, recall, Fmeasure or Gmean, to better assess the performance of the tool in unbalanced datasets and in the minority class (severe gender-based violence cases).

Figure 2 shows the trade-off between sensitivity and specificity and accuracy for different cutoffs. At 0 cutoff where all cases are classify as severe, we observe that for low scores sensitivity is 100% (all severe cases are detected) and specificity is 0% (all non-severe cases are undetected). Accuracy is only 24.9% which clearly shows the accuracy paradox. When cutoff increases, sensitivity decreases and specificity increases. The cutoff assessed to discriminate between severe and non-severe cases is 10 [Echeburúa et al. (2009)]. However, we observe that at 10, sensitivity is very low (47.98%) because only 129 out of 269 severe cases are correctly predicted (see Table 1). On the other hand, specificity is 81.40% which means that 661 non-severe cases are correctly classified out of 812. This cutoff achieved an accuracy of 73.1%, yet FNR is high (52.04%) which implies that 140 severe cases are wrongly classified. From a socio-technical perspective, this is translated as more than half of severe cases are labelled as non-severe when the score of the EPV is 10. Finally, the authors proposed to classify the risk of the EPV in three groups: low (0-4 scores), moderate (5-9 scores) and high (10-20 scores).

Analysing the EPV performance, we could suggest that a lower cutoff could imply more severe cases correctly identified for a cost on non-severe cases wrongly identified. For instance, a cutoff of 6 implies sensitivity is 83.27%, whilst specificity is 45.32%. This will led to a higher rate of severe cases correctly detected. After the revision of the EPV [Echeburúa et al. (2010)], the new tool named EPV-R was re-designed by analysing the ability of each item to impact the finding of severity: the ‘discriminatory power’ of each item. As a result, the EPV was re-designed with different assessment levels for every item rather than only two. Yet the performance of EPV-R in terms of confusion matrix or classification metrics is not assessed.

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Figure 3: ROC curve of EPV at cutoff = 10 (AUC = 0.69 and sensitivity = 47.96%).
Table 1: Confusion matrix of the EPV (cutoff score = 10). The number of FN (140) is higher than the number of TP (129), which implies that the tool is more likely to classify severe cases as non-severe when the obtained punctuation is 10. Source: Echeburúa et al. (2009).

| Actual | Predicted severe | Predicted non-severe |
|--------|------------------|----------------------|
| Severe | 129 (TP)         | 140 (FN)             |
| non-severe | 151 (FP)       | 661 (TN)             |

4 Is judicial reasoning aided by EPV-R?

The EPV-R appears to be, primarily, a tool for the police to assess the risk of dangerousness of a particular individual they encounter in domestic environments. In fast moving scenarios with limited information, police will use algorithmic tools to try to distribute their resources effectively and minimise risk, and EPV-R was developed by psychologists in an effort to assist. It is however frequently used in other situations. This paper considers the consequences of its use in the judicial process specifically, and what it might say for the use of similar risk-based algorithmic tools in court.

When deciding whether to prohibit the accused from approaching or communicating with an intimate contact, such as their wife or partner, judges will also have to make an assessment of risk. Indeed, where domestic violence is a potential factor, the assessment of objective risk is a legally-required element in judicial decisions restricting an individual’s movements, as set out below.

This paper considers real examples of judicial decision-making behaviour. A judge will hear representations of lawyers, documentary evidence, and sometimes oral evidence from witnesses, the accuser and the defendant. At the end of the hearing, on deciding what measures to take, the individual in the judicial role is also presented with evidence of the EPV-R score, suggesting the risk level of the defendant. This score is presented without a narrative. It is left to the judge to decide how to weigh this score, but the score is impossible to interrogate at court. It may contrast strongly with their own judgement. How this conflict is resolved will vary according to the individual judge, but will have serious consequences for the parties to the case. We consider status of the algorithm as a quasi-expert, and the tendency for humans to treat computer-derived scores with more weight.

4.1 On what basis does the Judge consider the assessment of risk?

In the legal framework, and specifically Ley 544 ter 1, judges are required to exercise their discretion in assessing the dangerousness of the offender. The Judges or Courts... taking into account the seriousness of the facts or the danger that the offender represents, may agree on their sentences... the imposition of one or more of the following prohibitions: a) The approach to the victim, or those of their relatives or other persons determined by the Judge or Court. b) That of communicating with the victim, or with those of his relatives or other persons determined by the Judge or Court. c) To return to the place where the crime was committed or to go to the place where the victim or his family resides, if they are different.

It is therefore relevant to consider to what extent the judge is likely to substitute their assessment of risk for that of the algorithm. European regulations highlight concerns with decisions made ‘solely on automated processing’; human decision-makers in these scenarios are required to exercise a real assessment of the merits. The European Data Board warns that this cannot be circumvented by ‘fabricating human involvement’ but these hybrid-type human interactions are where crucial focus needs to rest. Considering the recent draft AI regulation proposed by the European Commission, even if we assume this kind of algorithm to be classified as high-risk, the draft regulation sees transparency, human oversight and accuracy as mitigating factors. This paper suggests that given the sphere being operated in, these are ambiguous terms that may not provide sufficient protection; essential in this field is a nuanced and multi-disciplinary approach. In any event, the path of progress for adoption of the framework within the draft regulation is uncertain, it may finally be adopted in a modified form.

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10 see for an exploration of where the output of an algorithms falls within this framework Vanderstichele (2019)

11 544 ter 1, Ley Enjuiciamiento Criminal (LECRM).

12 European Parliament and Council, 2016:Art 22, https://gdpr-info.eu/art-22-gdpr/ (Last accessed, February 22, 2022).

13 See for up-to-date progress of this regulation: https://epthinktank.eu/2021/11/18/artificial-intelligence-act-eu-legislation-in-progress/ (Last accessed, February 22, 2022).
As we analyse this tool, it is also wise to have in mind the general principles common to most justice systems such as the rule of law, also codified in the Spanish Constitution. Article 1.1 asserts ‘Spain is hereby established as a social and democratic State, subject to the rule of law, which advocates as the highest values of its legal order, liberty, justice, equality and political pluralism.’ Article 9 further asserts the principle of certainty that the rule of law will prevail. 

Oswald highlights that we have to be careful not to rely on these types of tools just because they might be right (2020, p.227). She alludes to two systems at work: 

one in relation to criminal court proceedings, in which expert testimony is admitted only if based on scientifically valid foundation relevant to the issue at hand, and one which runs parallel to the court system without such constraints, based on realist and utilitarian principles.

The rule of law requires accessible, predictable judgements with clear justifications, on this the legitimacy of the system as a whole is built.

4.2 The Expert Algorithm?

...something changed, something, I said to myself, this doesn’t make sense, there is some type of mistake here...\[15\]

How is the score of the algorithm considered by the judge? Many of the arguments rest on how much weight is placed on the assessment of EPV-R in the judge’s reasoning. It is presented as evidence by the police at the hearing and on occasion, in the absence of supporting evidence from the victim, it is the only indication of risk in a given scenario. Even if other information is available, it is possible that the judge will substitute the finding of the algorithm for their own, or at least be heavily influenced by it.

In an analogous situation the the US Supreme Court considered a warning or "written advisement" to exercise some caution would be sufficient to satisfy procedural requirements in the controversial COMPAS algorithm. (State v. Loomis (2016)). Setting aside for one moment that no such warning is provided in the case of the EPV-R, there are still concerns with use, even when a warning is given. It is known that there is a tendency for humans to convert ‘a computer program’s suggested answer into a trusted final decision’ (Citron, p.1788–9 cited by Hartzog et al. (2015)). Whether or not true in every instance, clearly any level of algorithmic input into decision-making has the potential to cause a material effect to the final result. Importantly ‘the human-in-the-loop is a desired insertion at moments of legal indeterminacy in order to complete the narrative, using intuition and appreciation for the full range of human experience combined with legal knowledge’ (Hartzog et al., 2015, 1786). Eubanks illustrates the problems with assuming overseeing, human discretion will be exercised, when discussing operator’s responses to the Allegheny algorithm Vaithianathan (2017): ‘the model is already subtly changing how some intake screeners do their jobs’. Eubanks observes that screeners want to go back and change their scores, having seen what the algorithm has found.

As Garay and Suay point out, before computer algorithms, human experts had been brought into court to give their assessment of dangerousness, and at that time, academics and researchers viewed the expert with suspicion. In 1982, the American Psychiatry Association affirmed the unreliability of psychiatric predictions of dangerousness long-term as ‘now a recognized fact in the profession’ (APA,1982:5, cited in Garay and Suay, 2018, p.5) ‘Experts’ in the field might make assessments based on little data, but their authoritative tone, the ‘aura’ of the expert, would often mean crucial questions were decided to the exclusion of judicial, or juror assessment.

It seems that the human expert has been replaced by the algorithm, but the assumption that this is a more reliable assessment is worthy of thorough exploration. It is not suggested in this paper that the algorithm will always be inferior to the judge’s assessment, but it is not correct to suggest that a human will inevitably act as a ‘failsafe’ to an erroneous score, even when warned that they must act as one. The EPV-R’s designers’ openness is a positive example as it allows for far more scrutiny than in the case of the COMPAS algorithm. It illustrates how interdisciplinary approaches and user-engagement is key to highlighting risks and cautions regarding the implementation of a tool which was effectively designed for another purpose.

\[14\]The Spanish Constitution, 1978, https://www.boe.es/legislacion/documentos/ConstitucionINGLES.pdf (Last accessed, February 22, 2022).

\[15\]Direct and approved transcription of our interview with a judge working in Basque courtrooms.
4.3 Questioning the Expert

In looking behind the algorithm, judges are faced with a number of obstacles.

I can assess that there is sufficient risk to limit the freedom of movement, but the police say no, the risk is low. Of course, the lawyer can use this and say, look, the police say the risk is low. ... Now, I don’t know what is behind this assessment, I don’t know.

The judge spoken to in the preparation of this paper confirmed that despite repeated attempts, it is not possible to find out what the score has been based on, where information has come from. In fact, at least in court, none of the parties are aware, police, accused or witnesses. While the authors of this paper have seen forms which appear to be used for this purpose [Martínez 2019] p.74), those in the courtroom do not have the breakdown of the police assessment, nor of course, the background information that supports it. They are not therefore available to be scrutinised. The bare fact of the EPV-R output is simply made known. For example, if the accused is identified as low-risk the defence lawyer will use that to argue that no protection measures should be taken, irrespective of the evidence given in court. The judge cannot look behind this assessment.

In the absence of information about the score itself, it is natural for judge to ask how accurate it is, or otherwise assume high accuracy, based on its presentation by the police, and the fact that is commonly used [Garay and Suay] 2018.

4.3.1 Accuracy

If the judge questions the tool’s accuracy, the information available comes from technical, academic papers. The judge may be told that is highly accurate, quoting statistical terms such as ‘specificity’ or ‘sensitivity’, but these are not terms habitually used in courtrooms, and therefore not instinctively understood. Above, the precise functioning of the EPV-R algorithm is analysed, in so far as is possible with the data openly available. For current purposes, it is sufficient to understand that when EPV-R is described as accurate, this is in one particular calibration, where there is a relatively high level of false negatives, namely, a high number of individuals being identified as low risk despite being high risk (see Figure 4 for an illustration of this). A judge faced with what they consider to be a dangerous defendant, but an EPV-R rating of low risk, would be unaware of this when assessing the output of the algorithm, unless of course they have both considered the various academic papers on the subject and have experience of interpreting these kinds of statistics. Unlikely, given the pressured environment of the courtroom. Again we return to [Oswald] there seem to be two systems running simultaneously.

Further, there is a dearth of studies that measure success of the algorithm as actual violence as compared to projected risk. This means any assessment of accuracy is based on internal statistical assessments; real data is difficult to
obtain, partially due to ethical constraints. Without these objective measures of accuracy, the quality of the original information gathered by the police is even more highly relevant in the overall assessment of reliability.

### 4.4 Behind the Expert

For the courtroom judge, the enquiry cannot go beyond the ‘accuracy’ of the tool itself. However, given the luxury of time and access to further information, this paper looks behind the algorithm. There are a number of concerns raised when one analyses the inputs and mechanisms of the algorithm.

#### 4.4.1 Non-granular

The appendix lists the 20 items that go into the EPV-R’s overall assessment of risk. Considering these in detail, the data collected appears insufficiently granular. For example, Item 1 is a binary choice which focuses on the nationality of the defendant (Spanish or not), in a way that seems unsupported by statistical data (see technical analysis above). Equally, Item 5 refers to attacks made in the presence of other family members, but does not take into account violence if perpetrated in public spaces. In the original version of EPV, the choice was binary for all elements. The revised version, EPV-R moved some from a binary description to a scale of 0 to 3, but the users’ guide (descriptions from this are provided in the appendix) has not been revised, it does not give guidance on how to decide between 0, 1, 2 and 3 in terms of assessment.

#### 4.4.2 Human and subjective

Not all of the choices are objectively measurable. In fact many of the elements are effectively subjective human judgements, and in scenarios where there are not clear parameters for choices.

Item 6 is a composite measure, it asks the respondent to assess both seriousness and frequency, meaning there could be inconsistent application, while Item 7 asks that an respondent assess if threats have been made and that the ‘profile’ of the individual means they might perform those threats. The problem with questions which allow for considerable discretion is that this allows for respondents to incorporate unconscious assumptions or prejudices. Of course judges are human too, and at risk of making assumptions, but within the facade of the algorithm, all these uncertain aspects are masked.

As a further example, if a victim is in fear of their assailant and does not want to tell the police, previous violent conduct will of course not be reported. Equally, false reports might be assumed to be true and result in a high-risk rating. These are understandable sources of uncertainty, but crucially with the algorithmic output there is an air of objectivity given to something which may not represent reality. Items 4, 9, 10, 11 and 14 also seem vulnerable to this subjectivity.

#### 4.4.3 Unsuitable for use in judicial determinations

Assessment of risk in these scenarios involves not just the application of subjective judgement, but uncertain concepts and definitions, which have counterparts in legal determinations. Item 9 asks the respondent to assess if previous conduct has shown ‘clear intention of causing severe or very severe injuries’. To assess intent is inherently difficult, and the subject of many judicial determinations, using this as a component to a score will result in an answer that is far from an objective assessment. Essentially, we impute intent from actions. It is therefore strange that the tool does not prioritise identification of particular categories of actions in this item. Using ‘intent’ as a measure risks respondents falling back on gut feeling, substituting a hard decision for an easy one, potentially based on their own unconscious assumptions.\(^{16}\)

#### 4.4.4 Absolute and Relative Risk

Another cautionary factor is that the development of EPV, as described in the technical section, involved using a pool of individuals who had already been identified by reports. Therefore, it reflects relative risk, of those reported, these are low-risk individuals. Low-risk within that pool of individuals is higher risk than if you had a pool of all individuals. This is something known by the designers of course, it is not hidden, but given the way in which the tool has been introduced, it is not clear to the judiciary, who could easily correlate low-risk with an absolute, almost negligible risk. This might explain the extreme confusion felt by the judge. Low-risk, given it is from a narrow pool of people who have been reported to police in some way and under suspicion of violent conduct is not analogous to innocent/non-violent - but crucially may be interpreted in this way by judges using the tool.

\(^{16}\)There is an ethical difficulty of randomised control trial as no action is not an option where risk is assessed as high.
The corollary of this issue, is that if that other measure of performance, ‘area under the ROC curve’ is cited as being close to 1 and therefore evidence of reliability for the judge, it is equally unhelpful. It measures performance on the relative risk, not the absolute risk, which is what judges are concerned with Garay and Suay (2018).

4.4.5 Incomplete but determinative

Looking deeper into the algorithm not only are many of these elements filled out subjectively and inscrutably, but on occasion no answer is given at all. In an effort to improve EPV, the step was taken in EPV-R to give averaged scores in these cases (Paniagua (2017) et al). However, While Paniagua recognise the reasoning behind these issues and try to mitigate them (p.388), there is no indication to the judge that crucial facts have been omitted, or the data is simply not present. Missing values in some areas may co-occur often (such as item 17 justification of violent behaviour and item 16 the presence of cruel behaviour and contempt; Paniagua (2017). In the courtroom, the result is presented as equally reliable, if it is based on 20 items, or a much smaller number, and no indication is given that it represents an averaged rating. There is no indication of how limited the information was that went into the assessment of risk.

Eubanks writes of an algorithm that ‘manifests a thousand invisible human choices... [b]ut it does so under a cloak of evidence-based objectivity and infallibility’ [p.168]. Here those choices are not only by the designers, and the re-designers, but by the respondents to the information gathering stage, where there is wide scope for discretion. With discretion, can enter unconscious prejudices which can lead to certain groups being over-identified as dangerous, while others are under-identified.

Analogous with the lie-detector test, these technologies are not necessary optimised for the purposes that a courtroom requires Oswald (2020).

5 Risks, harms and limitations of judge-algorithm interaction

In this section, we analyse the dangers of using algorithms in the context of gender-based violence to assist judge’s decisions. To do so, we propose an interdisciplinary discussion, from a technical and legal perspective, inspired by a real user’s experience.

5.1 From a technical perspective

At present, current debates on risks, harms and limitations of socio-technical systems have been focusing on bias and the disparate impact that algorithms might have on different demographic groups, inspired by several publications and journalistic investigations Chouldechova (2017b); Angwin et al. (2016); Buolamwini and Gebru (2018); Eubanks (2018). The authors of the EPV-R acknowledge in Echeburúa et al. (2010) that there are limitations regarding the bias in the sample used to design it. For instance, the data does not cover every region within the Basque Country, yet the algorithm is used across the region. This could have some unintended consequences because characteristics of gender-based violence might be different, e.g. rural/urban areas. However, in this section we seek to move the analysis beyond the critique on bias by examining three factors: (1) opaque implementation, (2) efficiency’s paradox and (3) feedback loop.

5.1.1 Opaque implementation

The EPV-R was implemented in the courtrooms of the Basque country to assist the decision-making of judges. The tool was implemented without sufficient training for users, which in this case are judges ruling in gender-based violence cases. Moreover, judges were not provided of a detailed description of the tool nor a detailed description of the 20 items that composed it. This unintended opacity can impact on judges’ decision depending on their expertise. For instance, judges who believe faithfully in algorithmic accuracy, may come to believe that the risk assessed by the EPV-R is far more accurate than their intuition or experience. As we have previously explained, if a judge is influenced by the algorithm in the case of a FN, which is a severe case predicted as non-severe, this can lead to leave a potential woman victim of severe gender-based violence with less resources.

When algorithmic tools are implemented in life-changing scenarios, such in the case of the EPV-R, it is highly recommended to inform and share with the user the design process. Although the process of building the EPV-R is published Echeburúa et al. (2008, 2010), judges need to understand how the algorithmic output is calculated. Costanza-Chock explains that one of the principles of design justice is to ‘share design knowledge and tools with our community’ (Costanza-Chock 2020, pp. 200-201) and Ignazio and Klein contend that ‘transparency’ is also a data feminist principle.
5.1.2 Efficiency’s paradox

Efficiency is a key concept used to justify the implementation of algorithmic tools. The idea behind efficiency is that (1) data-driven solutions outperform humans and (2) can do task faster than humans. As Stone defines:

"Technical efficiency does not tell you where to go, only that you should arrive there with the least possible effort [Wildavsky, 1989]. [...] Efficiency is a comparative idea. It is a way of judging the merits of different ways of doing things. [Stone, 1997, p. 61]

Efficiency is far from being an objective concept or measurement. Thus, algorithmic efficiency should be questioned: efficiency for whom and for what? The EPV and its following version the EPV-R were implemented for the sake of efficiency:

The scale proposed to predict severe violence risk against a partner seems effective (with satisfactory psychometric properties) and efficient (short and easy to apply) for the goal sought [...]. This scale can be easily applied by personnel from the police, judicial, or social service settings, provided that they are sufficiently trained in its administration. ([Echebarria et al., 2009, p.934]

However, we observe that the tool was neither easy nor efficient for judges to apply, in a true sense. Judges need to have deeply informed observations so they can deliberate in the fairest and most objective way possible. When judges read an algorithmic output in the report of a gender-based violence case, they need to understand how the tool was trained, with which data, the algorithmic performance. Rather than reading ‘the EPV-R estimated that this case is severe/non-severe’, judges as users of an algorithmic evidence need to be offered training courses to improve the judge-algorithm interaction, avoiding blind decisions that are strongly influenced by the EPV-R’s output. Otherwise, they will spend time on understanding how the algorithm made the decision which can be very inefficient. Many judges do not have a background in computer science, so if a course of training is offered, understanding the nuances of algorithmic decision-making may not be straightforward. Moreover, time spent on understanding the tool may also affect the efficiency of judges themselves, as the workload in some Spanish courts is very heavy.

The efficiency’s paradox implies that while algorithmic tools are implemented for the sake of efficiency, the overall process results in being inefficient. Firstly, there is evidence that algorithmic tools do not always outperform humans. In fact, [Dressel and Farid concluded that a commercial risk assessment software used in courtrooms to predict recidivism was not more accurate than people with no expertise in criminal justice. Secondly, whilst algorithms are faster (more efficient) than humans in finding patterns and correlations within large quantity of data, algorithmic life-cycle can be turned into a tedious and inefficient task.

5.1.3 The feedback loop

Lum and Isaac analysed a predictive policing system that identified high-risk crime areas through statistical methods and historical police activity data. They claimed that the tool created a feedback loop: ‘This creates a feedback loop where the model becomes increasingly confident that the locations most likely to experience further criminal activity are exactly the locations they had previously believed to be high in crime: selection bias meets confirmation bias. [Lum and Isaac, 2016, p. 16].’ We argue that the EPV-R could be susceptible to also fall under a feedback loop.

The EPV and EPV-R are designed by using data of gender-based violence cases reported to the police. During the data gathering process, the police conduct an interview to the aggressor and the partner. They also gather evidence through friends, family and neighbours. Although police officers receive training regarding gender-based violence and the application of the EPV-R [European Institute for Gender Equality, 2019], the tool could enter into a feedback loop. Police could unintentionally insert their confirmation bias by believing that certain features are more common in cases of severe violence. For instance, migration is considered a risk factor [17]. If this information is fitted into the algorithm, it will automatically identify that these characteristics are more prominent in cases that had previously believed to be severe. Then, if cases predicted as severe by the tool are fitted again to retrain the scale in the future, it will reinforce the police’s confirmation bias. Thus, the feedback loop could impact negatively on gender-based cases that do not meet police’s beliefs. In order to avoid feedback loop, design justice principles could be implemented in the design process of the tool [Costanza-Chock, 2020]. For instance, by including Basque independent organisations against gender-based violence such as the Basque Institute for Women [18] or women who suffered this violence. Moreover, we

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17 As we have previously analysed, nationality represents a risk marker for predicting the risk of gender-violence. Yet foreign perpetrators with severe offenses represent 31% of foreign cases reported, whilst national perpetrators represent 36% of national cases reported.

18 See: https://www.emakunde.euskadi.eus/english/-/informacioa/english-about-us/ (Last accessed February 9, 2022)
agree wholeheartedly with the conclusion achieved by Green and Chen that ‘if risk assessments are to be used at all, they must be grounded in rigorous evaluations of their real-world impacts instead of in their theoretical potential’.

5.2 From a legal perspective

5.2.1 Two systems, No guidelines

There is a lack of appropriate legal guidelines for use in a court scenario. In the case of EPV-R, we are told by a judge, a first-hand user of this information, that no warning regarding the reliability of the data is given. The Legal framework requires real deliberation by the judge, but the status of the algorithm as a quasi-expert closes down enquiry.

Rules exist in legal proceedings to prevent reported speech being taken into account due to the disproportionate weight that can be attributed to hearing someone accusing another. Equally, disproportionate weight can be attributed to these algorithmic utterances which contain within them a compound of uncertainties. Assumptions, trust in computer outputs, in a context of limited information and a pressured environment, calls into question fundamental principles. Whether or not there is a warning or guideline for the judiciary, all parties are in the dark regarding how the assessment has been arrived at. If indeed acceptable for police use, this is particularly inappropriate for a hearing where different representatives will, of course, use the proclamation of the algorithm to argue their respective merits. Even a focus on transparency, human oversight and ‘accuracy’ - all measures anticipated for high-risk algorithms under the draft regulation - will not necessarily be a panacea for this systemic issue.

5.2.2 An unsatisfactory replacement

Principles of the rule of law and due process require that individuals are aware of the case against them, and for the individual in the case, the right of free movement may be restricted. Equally, a victim’s word may be doubted on the basis of a score of “low-risk”. We have highlighted that this assessment can be based on (1) incomplete information - gaps are filled in with averaged scores (2) subjective judgements with unclear parameters, allowing for assumptions and inconsistent application (3) an assessment of ‘risk’ that is different to how a judge would conceptualise it. All this is given the impression of objectivity. The investigation here has shown that the judge is faced with a judgement with considerable impact for both victim and accused, and supplied with an algorithmic assessment which could be helpful, or could be actively misleading. As Oswald [2020] says, this uncertainty as to the validity of the judgement is not consistent with the justice system’s basis: two systems are colliding.

5.2.3 Consequences of concern

The consequences of combination of factors in respect to EPV-R must give pause for thought regarding its comprehensive use in Basque courtrooms. Given ‘models are opinions embedded in mathematics’ O’Neill [2016], the assumptions made by those designing the tool will influence outcomes, even if all involved have the best intentions. The generalised, statistical approach has the potential to erode the individualised model of justice, which is a core element of the system. More broadly, cooperation and trust in the system - the justice system and the algorithmic tool itself - will be eroded if participants feel they are not being treated with respect. People who see the system as illegitimate will not cooperate, will not come forward as witnesses / accusers, and those accused will be less likely to adhere to the rules of the system.

6 Discussion

The impact of algorithms on decision-making at this level is often downplayed. Writing in 2018, Garay and Suay saw risk-assessing algorithms at court as something rare, treated with due caution by the judges involved; the experiences described by the member of the judiciary we spoke to suggest that in 2022 it is much more widespread and significant. This tool goes to the very core of the judge’s function. If we do not accept that EPV-R is the best overall measure of risk under the legal framework, a judge must weigh its assessment against their own judgement, based on the facts of the case. To do so they must consider how reliable the EPV-R assessment is (as compared to the other evidence), and

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19Heresay, known as testimonio indirecto in Spanish law, is inadmissible unless substantiated by other evidence. One could call these utterances, algorithmic hearsay.

20‘[P]eople’s reactions to legal authorities are based to a striking degree on their assessments of the fairness of the processes by which legal authorities make decisions and treat members of the public’, p.284

21The authors’ greater concern in that paper was to inform policy decisions.
what ‘risk’ means in this tool. As Garay and Suay assert, statistical tools may perform well for distribution of finite resources, but they cannot speak to the facts of the individual case, which is the objective in a judicial setting.

This paper has been prepared by authors of diverse disciplines (law and computer science) to highlight a practice that has widely gone unreported, was not fully anticipated by the designers of the initial software, and its use is so far unsupported by empirical research. In fact, we identify several elements that makes the use of this algorithm in the decision-making of judges not recommended, such as the efficiency paradox or the feedback loop. Moreover, we emphasise the necessity to better understand the influence of risk assessment tools on judges Green and Chen (2019). Given our discussion on trust in computer outputs above, it is perfectly possible that the judge in question will assume strong probative value / weight on to the EPV-R assessment, such in the M’s case. Amalgamating scores and filling in blanks with averages is arguable if seeking to replace simple intuitive decision-making by a police officer on the scene, but a judge may have heard extensive evidence. Given a bare score by the algorithm, they will be unable to identify those times when EPV-R is based on strong evidence, and those where there is very little. This is crucial information that is necessary for the judge to make their assessment.

We have proposed an interdisciplinary framework to analyse a gender-based violence risk assessment tool from a legal and technical perspective. The experience of the judge who works in the Basque judicial system has contributed to better understanding the human-algorithm interaction. We propose an additional perspective that could potentially avoid unintended consequences on the use of these tools and overcome risks, harms and limitations that have been identified through this paper. First, users (police agents, judges, prosecutors, social workers and healthcare professionals) of risk assessments tools should receive specific training on algorithms, so that they are able to identify algorithmic risks and harms, rather than relying too heavily on these tools Green and Chen (2019). Second, reject the assumption that technology will automatically solve problems in all scenarios (techno-solutionism) and instead seek to avoid the efficiency paradox in the context of gender-based violence. Risk assessment tools are implemented sometimes to address the lack of human resources. Yet algorithms and risk assessment tools cannot think like people, as Dreyfus and Dreyfus contended: ‘human beings have an intuitive intelligence that “reasoning” machines simply cannot match’.

Ultimately, is essential that judicial users understand their important overseeing role, that an algorithm cannot replace them and that its automatic assessment can be wrong. Failure to recognise this could lead to very serious consequences in cases of gender-based violence (as we have seen throughout this paper, with false negatives) if they simply go by what the tool suggests. In considering further steps, we also recommend reviewing the work of D'Ignazio and Klein Costanza-Chock; Peña and Varon. Bringing together many perspectives on risk assessment tools in the context of gender-based violence will lead us to build better algorithms, promoting technologies and practices that ‘are more coherent given the present and the future we want to see’ Peña and Varon (2019).

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A Appendix A: The 20 psychometric items

The following list presents a translation of the description of the items found in the EPV-R’s user guide to which the authors of this paper had access:

1. Male aggressor or victim is an ‘immigrant’: Foreign origin is considered to exist when the aggressor or the victim originates from or is a national of a foreign country.

2. Recently separated or in the process of separation: It is considered that there has been a recent separation or that separation proceedings are in progress when, in the last 6 months, the couple’s relationship has undergone a crisis situation that provokes the beginning of the cessation of cohabitation, the beginning of separation proceedings or the existence of a judicial separation or divorce decision.

3. Recent harassment of victim or breaking the restraining orders: In the last 6 months, bullying behaviour has taken place, which can manifest itself in the following forms: threatening phone calls, repeated forwarding of messages or continuous pressure on children.

4. Existence of physical violence that can cause injuries: Any non-accidental conduct or act that causes or is likely to cause harm (pushing, hitting, hitting, burning, throwing objects, maiming, etc.). The means or instruments used in violent episodes are likely to cause injuries (knives, scissors, frying pans, irons, etc.).

5. Physical violence in the presence of the children or other relatives: The aggressor has exposed his nature and does not care that his behaviour is known by the rest of the members of the family unit. He has overcome the inhibition of attacking in the presence of family members.

6. Increase in the frequency and severity of the violent incidents in the past month: Violence is increasing and incidents (2 or more) are becoming more and more serious.

7. Severe threats or threatening to kill in the past month: The threats are sufficient to make the victim feel frightened and submit to the aggressor’s will. The profile of the aggressor suggests that he is likely to carry out her threats.

8. Threatening with dangerous objects or with weapons of any kind: When threatened with any object or weapon likely to cause harm to the physical integrity of the person.
9. **Clear intention of causing severe or very severe injuries:** The aggressor’s attitude towards the victim, even if it does not materialise in serious injuries, denotes a clear intention to cause them, such as when an object is thrown against the victim’s head, a sharp push is given, the victim is grabbed by the neck, thrown to the ground, etc.

10. **Sexual aggression in the couple relationship:** Any conduct or act of a sexual nature performed without the consent of the victim. The perpetrator uses intimidation methods (e.g. waking up children) to break the victim’s will.

11. **Very intense jealousy or controlling behaviours toward partner:** The aggressor feels very insecure in his relationship with the partner because he has an intense fear of losing his partner.

12. **History of violent behaviours with previous partner:** The perpetrator has a history of physical or psychological violence with previous partners.

13. **History of violent behaviours with other people:** The aggressor is (or has been) involved in violent incidents with other people in their family, social or work environment.

14. **Abuse of alcohol and/or drugs:** The offender is abusing alcohol or drugs when he is currently using alcohol and/or drugs in a problematic way, either on a regular basis. In both cases, it is abusive use when it interferes negatively with the subject’s behaviour towards the victim. However, this item does not assess positively in cases where there is habitual or sporadic use of drugs. Habitual or sporadic, but non-problematic, use below the limits of intoxication is not rated positively in this item, nor is intoxication or dependence without a clear effect on behaviour.

15. **History of mental illness and dropping out of psychiatric or psychological treatments:** There is evidence that the perpetrator has a psychiatric history. There is evidence from information or direct evidence that he has abandoned treatment or that he has stopped taking the prescribed medication or therapy for treatment of his illness or that he has stopped taking the prescribed medication or therapy.

16. **Cruel, disparaging behaviors directed at the victim and lack of remorse:** It is a style of behaviour of the aggressor that currently manifests itself in attitudes of contempt and humiliation, which leads the victim to feel subjugated, to which is added a lack of repentance. The aggression and violence of the person is exercised in an mechanical (non-emotional) and cold-blooded way, without being directly dependent on the situational circumstances (arguments, unpleasantness, etc.) that are behind the other type of violence.

17. **Justification of violent behaviour due to aggressor’s own state or to victim’s provocation:** They use defence mechanisms when they offer their version of events: denial, justification, minimisation, etc. They blame the victim for causing them to be "forced" to use force. They do not consider themselves violent and perceive that they have been provoked by their partner.

18. **Victim’s perception of danger of death in the past month:** Assess the victim’s perception when she has become aware that the perpetrator may kill (or seriously assault) her and feels in imminent danger of death (or serious assault). Probe on the basis of what facts the victim perceives this danger.

19. **Attempts to drop charges or going back on the decision to leave or report the aggressor to the police:** The victim currently wishes the proceedings not to be initiated or closed for fear of reprisals. It is necessary to inquire about other motives that the victim may have that could cover up the fear of the aggressor: maintenance of the family unit, lack of economic resources, emotional dependence on her partner, shame in their social circle, etc.

20. **Victim’s vulnerability because of illness, solitude, or dependence:** The victim is alone and has no one (family or friends) to turn to in case of separation. Physical, economic or emotional dependency.
Figure 5: Questionnaire of the EPV to assess the risk of gender-based violence in the Basque country. Source: Echeburúa et al. (2009).