over-indebtedness does not speak with one voice:

Profiling and predicting over-indebtedness

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online seminar on good practices in debt advice

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Over-indebtedness and Credit use

- Contracting debt is common among many households in the process of obtaining necessary goods and services, such as a place to live or getting a college degree.

- However, the estimation of what is a financially acceptable level of debt for a consumer, given her prospective income stream, may be a difficult matter.

- An unfortunate consequence of such difficulty, is the rising of **over-indebtedness** among European households.

over-indebtedness: *the recurrent inability to meet essential living expenses and repaying credits when they are due*

Consequences of over-indebtedness

- Over-indebtedness has considerable consequences both for individuals and for society:

    - Over-indebted households report reduced standard of living, deterioration of well-being, health, financial exclusion (i.e., limited access to bank and credit services); and social stigma

    - Systemic over-indebtedness may create a feedback loop in which indebted households cut back in consumption, decreasing demand, which, in turn, decreases production… cooling down the economic activity (…increasing unemployment, etc.)
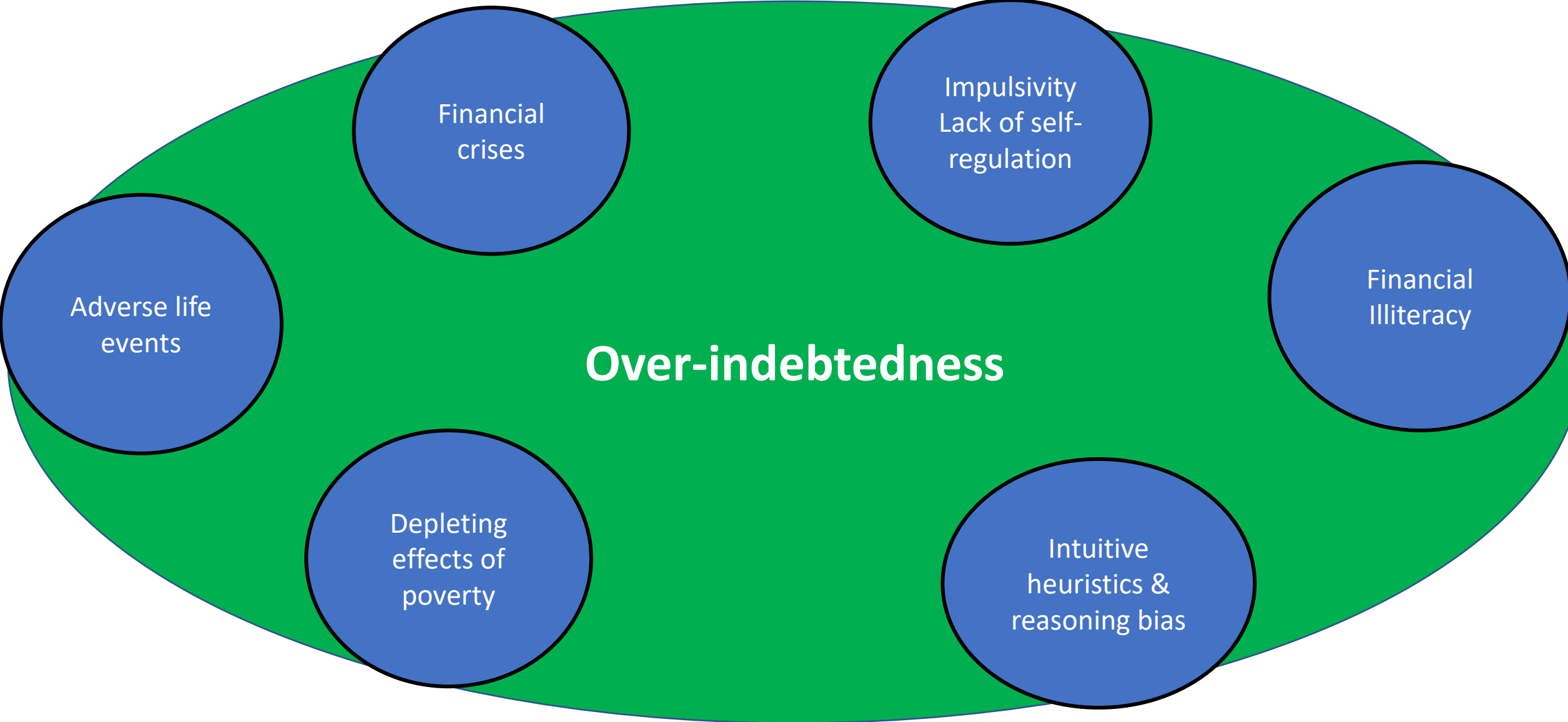
Risk factors of over-indebtedness

Risk factors of over-indebtedness

- Research have linked all these risk factors to over-indebtedness.

- However, most studies have provided evidence for the causal role of each of these factors "*ceteris paribus*" (i.e., assuming that all the remaining factors are held constant)

- Actual cases of over-indebted households are likely to be multifactorial.

- **How different risk factors combine in producing concrete situations of over-indebtedness** is a highly important issue that has received less research attention.

- we hypothesize that **"over-indebtedness" may be a misnomer because it puts under the same conceptual umbrella distinct profiles of indebted households.**

Our goals

- Testing for the existence of **different profiles** of over-indebted households

- identifying the main features of the profiles (if and when they emerge from the data)

- to create **predictive models of classification of new cases** (households) of over-indebtedness or under risk of over-indebtedness

- to achieve these goals, the research approach combined unsupervised and super-vised Machine Learning (ML) techniques, to analyze a large number of descriptive and predictive models of over-indebtedness.

Study

- We analyzed the data of the **population of 1654** consumers nationwide who contacted the debt advisory services in Portugal during the years of 2016 and 2017

- When consumers contact the debt advisory services, they are over-indebted and cannot pay their bills anymore, having a high risk of poverty.

- The dataset comprises a broad range of variables to understand the full picture of consumers' finnancial health: family socio-demographics, total income, total expenses, employment information, credit details as well as consumers perceived causes of over-indebtedness.

Supervised Machine Learning algorithms used

Fig. 1. Supervised Machine Learning algorithms that have been used in this work.
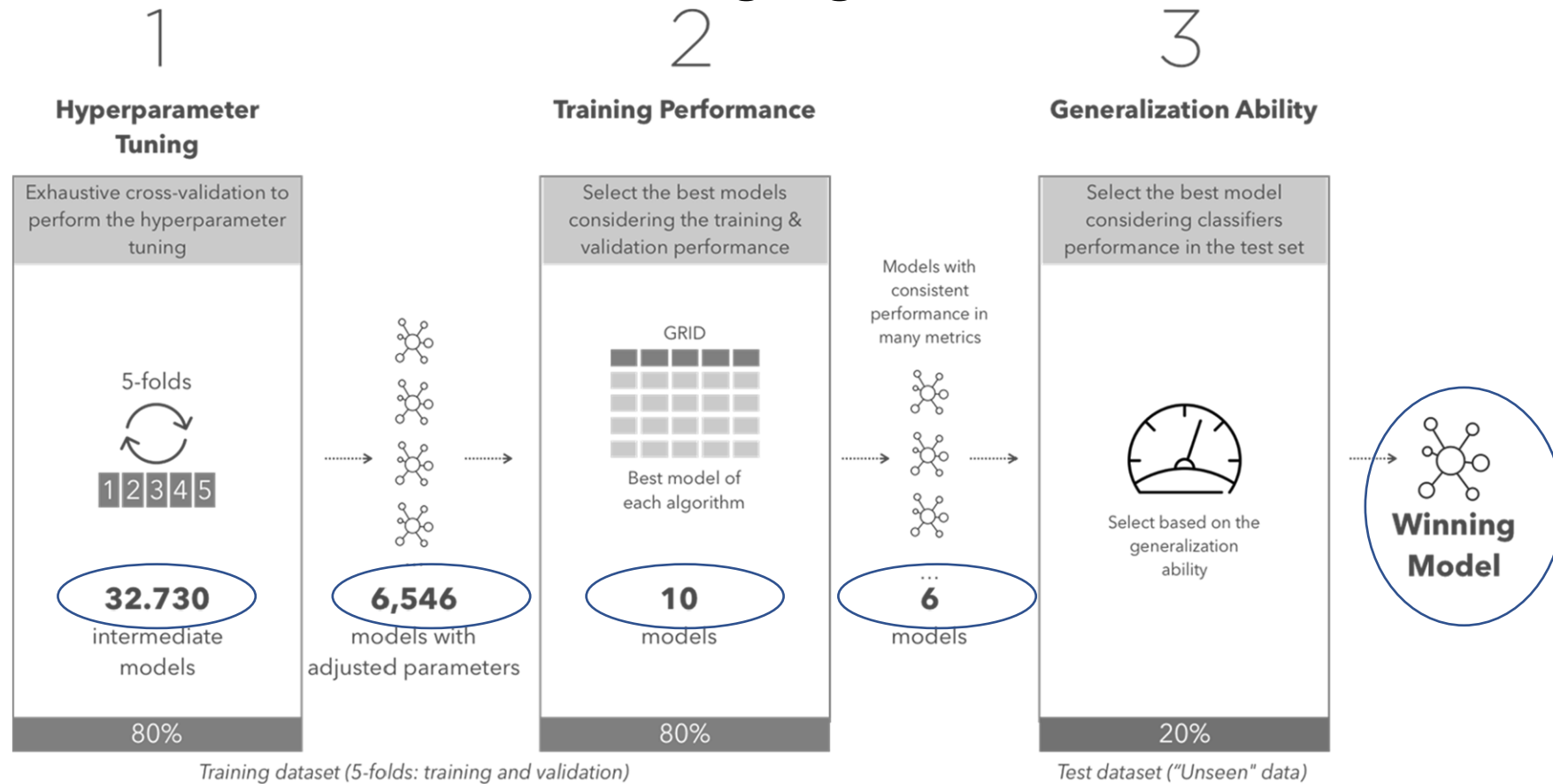
Machine Learning algorithms

Fig. 2. Grid Search Hyperparameters Tuning Process.

The wining model identified 3 profiles of over-indebedness

Low-income households	Low credit control households	Crisis-affected households

Low-income households		
Medium-sized households with the lowest: - income per capita; - total credit monthly installment - credit effort rate Lowest unemployment **100% atribute financial difficulties to causes not** directly **related to the crisis**		

Causes not related to crisis: death in the family, divorce, illness/incapacity to work...

Low-income households	Low credit control households	
Medium-sized households with the lowest: - income per capita; - total credit monthly installment - credit effort rate Lowest unemployment 100% atribute financial difficulties to causes not directly related to the crisis	**Smaller households with the highest income per capita** **Indications of low credit control:** - highest personal credit rate - highest credit effort rate lowest household expenses **84% atribute financial difficulties to causes not** directly **related to the crisis**	

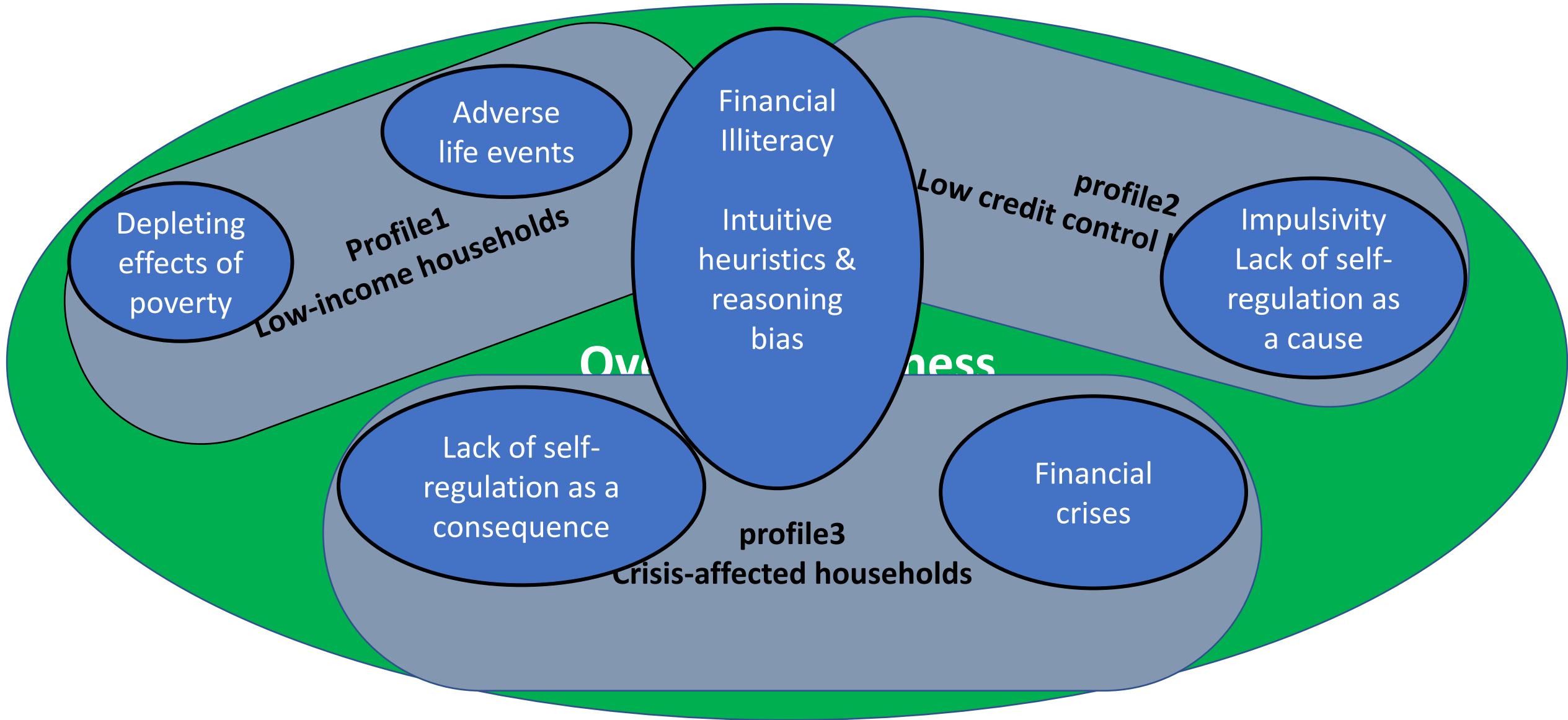**Causes not related to crisis**: death in the family, divorce, illness/incapacity to work...

Low-income households	Low credit control households	Crisis-affected households
Medium-sized households with the lowest: - income per capita; - credit effort rate - total credit monthly installment Lowest unemployment 100% atribute financial difficulties to causes not directly related to the crisis	Smaller households with the highest income per capita Indications of low credit control: - highest personal credit rate - highest credit effort rate lowest household expenses 84% atribute financial difficulties to causes not directly related to the crisis	**largest households; low income per capita; with the highest:** - household expenses - provision with housing and other credits - housing credit effort rate **83,7% attribute financial difficulties to crisis-related causes**

Crisis-related causes: unemployment, delays in salary payment, salary cuts, …

Over-indebtedness as a multifaceted phenomenon

Depleting effects of poverty

Adverse life events

Profile1
Low-income households

Financial Illiteracy

Intuitive heuristics & reasoning bias

profile2
Low credit control

Impulsivity Lack of self-regulation as a cause

Over-indebtedness

Lack of self-regulation as a consequence

profile3
Crisis-affected households

Financial crises

Summing up

- Using Machine Learning algorithms it was possible:

  - **To identify diferent profiles of over-indebtedness**
  - **To predict the profile of new cases of over-indebted households with high accuracy level (89.5%)**

Limitations

- **Lack of** more **detailed data** concerning several of the psychological and situational risk factors.

- We are looking forward to measure consumers:
  - tendency to rely on improper heuristics
  - self-control
  - innumeracy
  - attitudes towards credit, etc.

- To obtain more fine-grained information and improve the AI model ability to **describe, classify, and predict over-indebtedness**.

Implications for debt advise practice
How Artificial Intelligence can improve interventions to fight overindebtedness

- **Over-indebtedness** speaks in different voices as indicated by the surfacing of **different profiles** - involving **different risk factors**

- **There is no "one fits all solution"** when it comes to fighting and preventing over-indebtedness

- **The effectiveness of interventions** to counteract and prevent families from becoming over-indebted may be **increased if they are adapted to each profile**

- Government programs and Interventions could be tailored to better respond to the specific chalenges faced by the **different profiles**.

Implications for debt advise practice
How Artificial Intelligence can improve interventions to fight overindebtedness

- Each case of over-indebtedness is likely to be unique

- The idiosyncrasies of "real-life" cases of overindebted families are not fully captured by any of the 3 identified profiles

- **AI Profiling** should not be seen as a "solution" but **as a tool for debt advise practice**

- With this in mind, we developed a software App (beta version) that:
    - classifies new cases of over-indebtedness into one of the 3 described profiles
    - is able to also classifiy non-overindebted consumers based on their similarity (feature overlap) with the different profiles of over-indebtedness.

- This **App** provides a **quick outline of the financial situation of the household (including alerts and suggestions)**, and could be used by debt advise experts/consumers as and aid for decision making.

Research team

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Thank you for your time!

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