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Using Cognitive Work Analysis for Information System Design - a Dashboard for Visualising Liquidity

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Abstract

This paper presents the application of Cognitive Work Analysis (CWA) to create an Abstraction Hierarchy (AH) model that helps users to identify key functional relationships for managing financial systemic risk. CWA has been used in Information Systems work before particularly in the Human Factors and Decision-Making literature. The research goal is proof of concept. That is, to apply a well-developed theory from the Human-Computer Interaction (HCI) literature to a new domain, in the form of financial risk via a prototype. Users might include investors, government agencies, policymakers, and financial institutions. The AH model will ultimately lead to an artefact that embeds visual analytics (the science of analytical reasoning facilitated by interactive interfaces) and combines automated analysis with dynamic interaction with the data. Based on the notion that companies with high leverage (total debt/equity) are more likely to become financially distressed than those with low leverage, we propose two potential visualisations to be incorporated into the analytics instrument. The first illustrates the dynamics between leverage and growth at the macroeconomic level; and the second between leverage and duration at the microeconomic level. This work has the potential to contribute to both the Information Systems (IS) literature and the Finance literature. The prototype developed demonstrates how the CWA approach from other domains can be incorporated into a visual analytics system development methodology, and how the resultant prototype can be successfully applied to visualise macroprudential risk. As a feasibility study, this work paves the way for an IS design science research project that will generate knowledge about our proposed method used to design a decision support system (DSS) for liquidity risk management and the system's design.

Keywords credit risk, liquidity, visualisation, cognitive work analysis, abstraction hierarchy.

1 Introduction

There is growing interest amongst investors and policymakers in the effects of business failure and financial distress on the health of economies (Gepp et al. 2008; 2010). Failure in the financial system can lead to catastrophic outcomes such as bank runs and bankruptcies, and if severe enough, the failure of the economy may take a nation many years to recover. Many examples exist in recent history such as HIH (Australia), Enron (USA), and Northern Rock in the UK. Other causes of system failure are socio-political ones (Manela and Moiera 2017). More recently Gepp et al. (2018) suggested that big data could be used to forecast financial distress at the organisational level. We draw on human factors research to model key factors that apply in this environment. CWA is a well-established framework and has been around and evolving since the 1970s (Rasmussen,1994). CWA has been applied in various domains but has only been used explicitly as a blueprint for information systems design in the last decade particularly in the domain of useability. Thus, this work can be taken as a case study on the application of the human-centered design of information systems to a specific domain, namely finance.

In Section 1.1, we describe the history of the applications of CWA to socio-technical systems. In Sections 1.2 and 1.3, we focus on the CWA applications in the finance domain. In Section 2, we describe our methodology; and in Section 3, we present a blueprint for the design of a finance-focused risk-mapper system.

1.1 Cognitive Work Analysis

CWA is a framework that was developed to model complex sociotechnical work systems. It has its roots in psychology in the 1960s and 70s. It has been developed to facilitate decision-making in complex environments such as nuclear reactor management and military environments with a focus on risk management and safety. The main novelty in CWA is focussing on the work structure and behavioural opportunities open to actors within that structure. The abstraction-decomposition space (ADS) is the main tool for modelling the purposive and physical work context or problem space of workers. CWA has more recently been adopted in the field of human factors engineering and by extension, user interface design. As a domain-independent approach, CWA has been applied in designing dashboards for library management (Wong and Gulden 2017) and clinical displays (Effken et al. 2001). It is seen as a promising approach for the analysis, design, and evaluation of complex, socio-technical systems (Naikar 2005). CWA has been applied in the field of finance. Achonu and Jamieson (2003) have proposed an Abstraction Hierarchy (AH) model using Work Domain Analysis (WDA) for monitoring and decision-making by portfolio management teams for portfolio management. The AH model presents five levels of information: functional purpose, abstract function, generalized function, physical function, and physical form. Li et al. (2015) have proposed a WDA model, based on the cognitive engineering approach, for automated financial trading. The emphasis on WDA has gradually extended to become one of the multiple dimensions of CWA (Naikar 2011). Modern financial trading systems involve a variety of coupled socio-technical systems and have become highly automated. Since CWA has been used in complex and risky environments before, we propose its use to mitigate risk in financial systems via macroprudential regulation. We apply CWA to system design in the financial systemic risk domain as a proof of concept. Notably, neither Achonu and Jamieson (2003) nor Li et al. (2015) dealt explicitly with risk.

1.2 Liquidity and Credit Risk

Imbierowicz and Rauch (2014) have investigated the relationship between liquidity risk and credit risk in banks. We note that liquidity risk and credit risk are the two main sources of bank default risk. Liquidity is defined as the ability to settle obligations with immediacy. It follows that a bank is illiquid if it is unable to settle obligations in time. Further, liquidity is divided into market liquidity and funding liquidity. We define funding liquidity as the possibility that over a specific horizon the bank will become unable to settle obligations with immediacy. Market liquidity refers to the efficiency or ease with which an asset or security can be converted into ready cash without affecting its market price. The most liquid asset of all is cash. On the other hand, real estate is subject to market foibles, and investors would find it harder to realise its paper value in a quick sale situation.

Spuchľáková et al. (2015) explored the nature of credit risk. The definition we will use here is from their work: "Credit risk or default risk involves inability or unwillingness of a customer or counterparty to meet commitments in relation to lending, trading, hedging, settlement and other financial transactions." Credit Risk is made up of transaction risk or default risk and portfolio risk. A good risk management strategy incorporates the principles of risk management processes including risk identification, monitoring, and measurement. For the purposes of our prototype design, we need to effectively describe a hierarchy of measures used in the financial industry for decision-making, both human and automated. We will be creating an artefact that allows an analyst to look at credit both from the industry (e.g., health, education, agricultural) and country (i.e., nationality) perspective.

1.3 Visual Analytics

Flood et al. (2016) have provided an overview of visual analytics and discussed its potential benefits in monitoring financial stability. Visual analytics is the science of analytical reasoning enhanced by interactive visualisations tightly coupled with data analytics software. It harnesses the functions of rapidly streaming high-volume data and allows human analysts to interact with this data in a flexible, rapid, and powerful way. Visual analytics has the potential to increase supervisors' comprehension of the data stream, helping transform the raw data into actionable knowledge to support decision-making and policymaking. The possibilities and pitfalls of applying visual analytics in financial systems are acknowledged. The work presented contributes to Flood et al.'s (2006) proposed agenda of articulating domain tasks, completing data and task abstractions, and developing visualisations and analyses which will help systemic risk analysts detect, identify, monitor, and manage threats to global financial stability. Other researchers have addressed that "call to arms" in a variety of disciplines including accounting, banking and finance, economics, and computing

2 Methodology

We use a multidisciplinary approach, making sense of the data collected and derived to obtain insights from multiple perspectives for decision-makers. The four steps in the design of a visual analytics system originally proposed by Flood et al. (2016) have been augmented to show how the other key originalities of this work (CWA, AH, and Visualisation) will be built (See Figure 1).

2.1 Determining What to Represent

CWA demands the diagnosis and localization of problems. To do this, developers normally interview experts and examine materials in the domain such as reports and other documents. In our case, we have drawn on the structure of the Bloomberg data and knowledge from finance experts to complete this step. One of the authors is a finance industry expert (researcher-as-instrument) who provides in-depth knowledge from the finance perspective.

2.2 Choosing Visual Forms to Represent Objects

The next step is how to visually represent those problems defined in step 1 to identify trends and patterns. This involves design choices around how to meaningfully present distinct types of information simultaneously. For this, we draw on the risk map visualisation technique comprehensively described in Wong and Gulden (2017). This approach requires the development of an AH to define the domain.

2.3 Designing Underlying Computational Algorithms

To give the analyst flexibility in how the information is displayed, each interface element needs to be associated with a design primitive, and behind that primitive, is an algorithm based on sound financial modelling. Here the developer needs to decide on the underlying computational algorithms that are useful to macroprudential policymakers, according to the finance literature. Algorithms of interest include those used to calculate financial ratios, solvency and liquidity, interest rate risk, etc. Once a problem domain has been structured in an AH, techniques of human-computer interaction design are used to represent the relevant functional relationships visually. This involves mapping key component attributes, facets, derived risk measures, etc., to rendering elements (for example, size, colour, and motion).

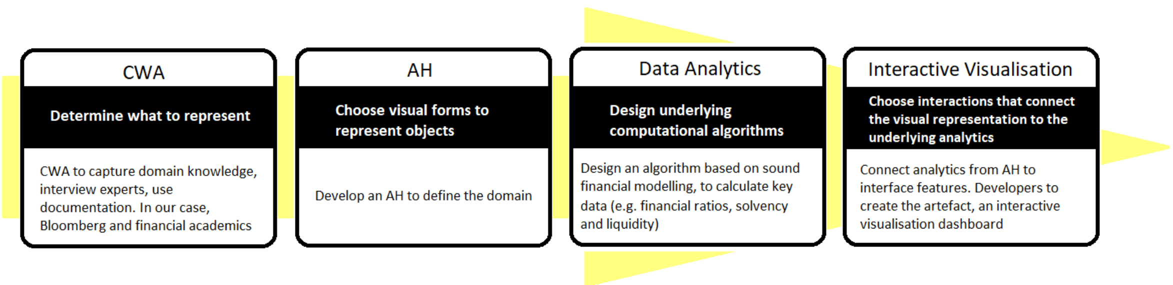

Figure 1: Design of visual analytics systems.

2.4 Choosing the Interactions that Connect the Visual Representation with the Underlying Computation Algorithm

In the last step, it is necessary to combine underlying computation derived from the AH and connect the visual representations to create ad-hoc visualisations. Beyond this, the actual creation of the artefact is in the hands of the developer, in our case the visualisation tool will be built using the programming language Python, and the open-source software Plotly and Dash.

2.5 Data Source

We extracted the required data from the Bloomberg database, covering all 8701 companies in 16 countries in Europe, between 1980 and 2016. The data included values for common shareholders' equity, short-term debt and current portfolio and long-term debt. The data was cleansed, and the following three key data points were stored for analysis:

- short-term leverage = short-term debt/equity (or short-term D/E ratio)
- long-term leverage = long-term debt/equity (or long-term D/E ratio)
- total leverage = total debt/equity (or D/E ratio)

These data points provide the underlying analytics to support the interactive visualisation dashboard.

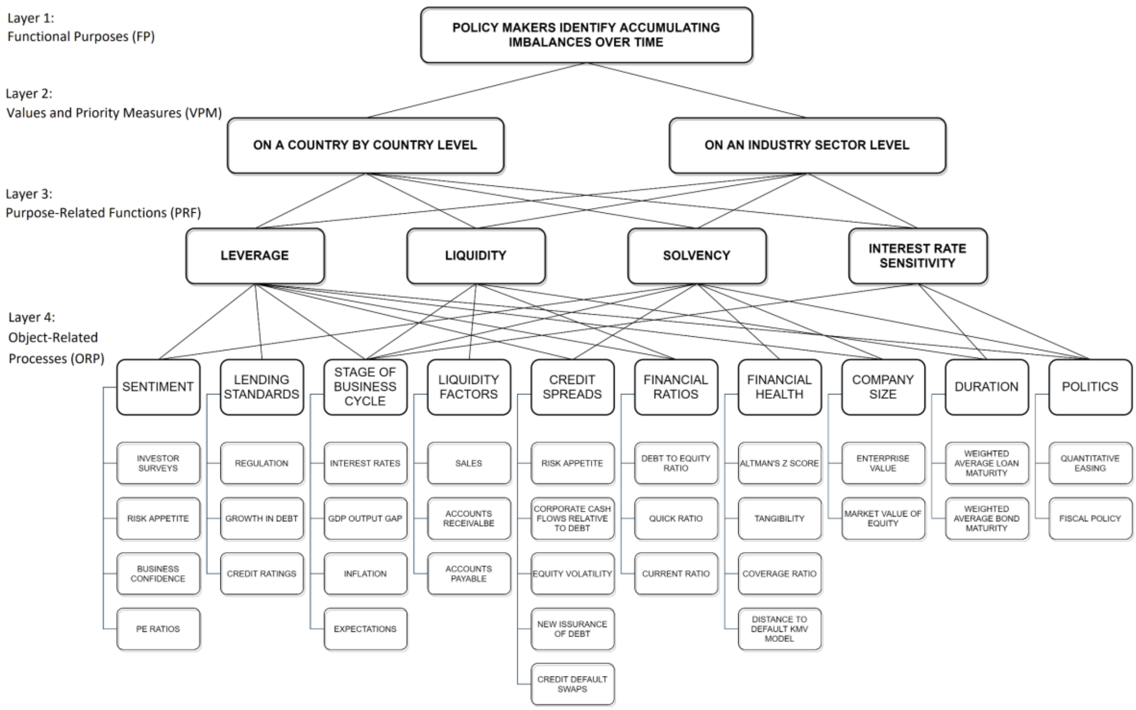

Figure 2: Abstraction Hierarchy Model.

3 Results

3.1 Abstraction Hierarchy

The abstraction hierarchy shown in Figure 2 is adapted from the original Rasmussen (1994) template to include four layers that represent the functional structure of financial systemic risk analysis to identify the level of imbalance. An AH provides a how-what-why (bottom to top levels) structure to show how nodes at higher levels are achieved by nodes at lower levels. The AH in Figure 2 has been developed to understand the nature of liquidity. In the final implementation, it will be necessary to represent liquidity via computed proxies.

3.2 The Four Layer Abstraction Hierarchy

In a departure from the commonly deployed five layers of abstraction (Rasmussen, 1994), only the top four layers are specified. Physical objects (the bottom layer) are omitted from the model because a portfolio is not primarily a physical system. Describing Figure 2 from the top down, layer 1 represents the Functional Purposes (FP), the reasons why the system exists. The functional purpose of visualising liquidity is for policymakers to identify imbalances over time, and to investigate whether leverage is country-specific or industry-specific, as specified in Layer 2, the Values and Priority Measures (VPMs). From a debt point of view, finding an unusual and growing imbalance in the economic system. Layer 2 is then broken down into Purpose-Related Functions (PRF), as specified in Layer 3. The PRFs are functions that the system must accomplish to achieve its stated purposes. The PRFs examine the four key concepts that will be used to assess financial systemic risk.

- Leverage relates to the magnitude of debt in the business.
- Liquidity refers to the ability of the firm to repay current liabilities, which are those due in the short term.
- Liquidity is contrasted with solvency, which refers to the company's ability to meet long-term obligations.
- Interest rate sensitivity, looking at the weighted average maturity of when debts are due.

Layer 4 is Object-Related Processes (ORP) which identify the measures needed to perform and support the system's functions. The four PRFs are then broken down further into ten specific ORPs: sentiment, lending standards, stage of the business cycle, liquidity factors, credit spreads, financial ratios, financial health, company size, duration, and politics. The PRF liquidity is supported by four ORPs - the age of the business cycle, liquidity factors, financial ratios, and duration. Each ORP consists of one or more data points that can be collected and calculated. For example, the ORP liquidity factors consist of sales, accounts receivable, and accounts payable.

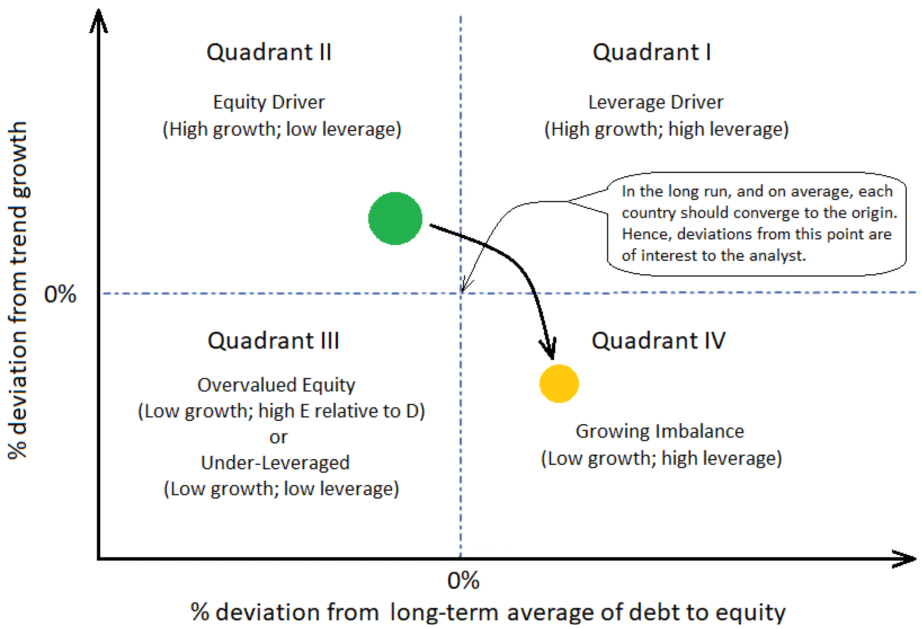

Figure 3: Macroeconomic view of a country.

3.3 Visualisation Examples

We propose two potential visualisations to be incorporated into the analytics instrument. The visualisation shown in Figure 3 considers the macroeconomic view of a country. The x-axis, as a proxy for leverage, represents the percentage deviation from the average D/E ratio within a particular country. The y-axis, as a proxy for the stage of the business cycle using the output gap, represents the percentage of deviations from a country's own trend growth. As noted in the text box, on average, each country would converge to the origin where the percentage deviation is 0%.

The dot colour is a visualisation feature connected to business confidence, which reflects both sentiment and the stage of the business cycle. The dot size is connected to the market capitalisation of the economy.

The scenario in Figure 3 shows a country that experiences a decline in economic growth which consequently leads to a negative output gap. The decline is revealed by the path of the dot moving from Quadrant II (big green dot) to Quadrant IV (small orange dot). The green dot is a country experiencing a boom. This growth is leading to higher equity valuations, which has reduced the D/E ratio from the long-term average. This is called the 'equity driver' as the economy's booming growth coincides with lower leverage ratios. The green colour indicates that business confidence is also strong. Unexpectedly, growth soon starts declining and a recession occurs. Equity markets crash and the leverage ratio increases, as future expected profits are now being discounted more aggressively by the markets. Hence the leverage ratio increases beyond the long-run average as the dot moves from Quadrant II to Quadrant IV. And the dot becomes smaller (lower market capitalisation) and the colour changes from green to yellow (lower business confidence). There is a growing imbalance, as the country experiences high leverage and a negative output gap. Note that a country that has a negative output gap, but positive sentiment (indicated by the dot colour) may be in an economic recovery.

There are two possible outcomes. One is economic growth recovery, pushing the dot back into Quadrant I, and possibly into Quadrant II as equity valuations recover, or the authorities step in and encourage a reduction in leverage and move the dot closer to the average (centre).

The second example, shown in Figure 4, provides a more microeconomic view for policymakers to assess companies within a country. The x-axis represents the long-term D/E ratio, and the y-axis the duration. The dot colour is connected to the solvency of each company, using Altman's Z-score (Altman 2013). The dot size is connected to company size, which is a physical object in the AH. From the macroeconomic view, the country has moved into Quadrant IV after a market crash. Initially, three companies (A, B, and C) were below the average D/E, whilst the country was experiencing high growth. But due to the negative output gap, leverage increased for companies A and B, which has increased the average D/E ratio above the long-term average.

For company A, this is not a problem yet as duration is high, and repayment is much further into the future. The analyst will have to keep a close eye on the current ratio over time, to see if the liquidity problem worsens as the company could continue to issue long-term debt and remain in Quadrant I. Company B is in a more critical position. Its D/E is roughly the same as company A, but it has a lower duration. Hence it needs to pay back debt in the near term. The Altman Z score confirms this by turning the dot colour red. The interactive visualisation can be further enriched by adding another dimension, the third axis for a liquidity measure such as the current ratio.

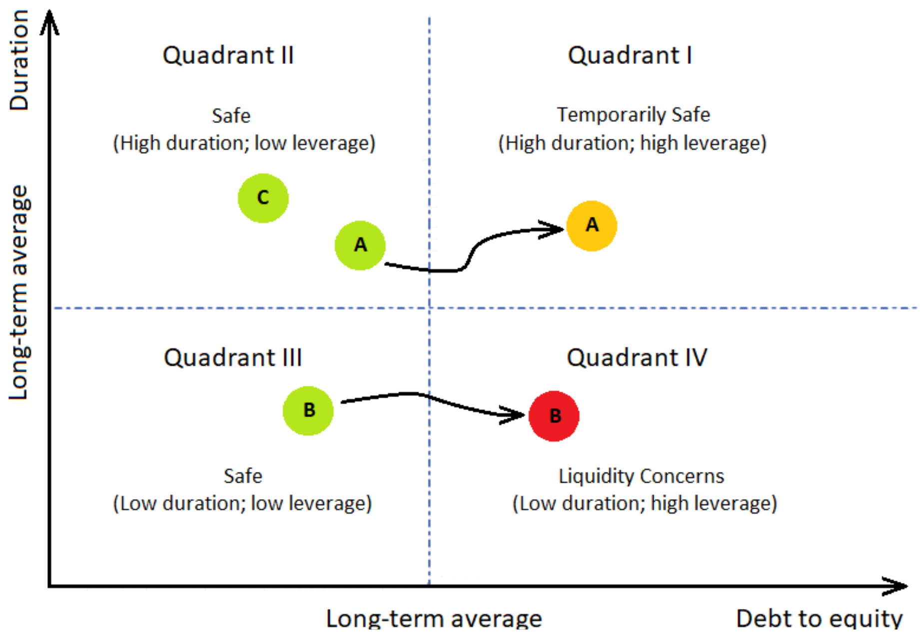

Figure 4: Microeconomic view of companies.

4 Discussions and Conclusion

We applied CWA to devise a dashboard to address the problem of predicting systemic financial risk in the finance domain. We assert that the dashboard (Risk Map) can provide cognitive support for the detection of exceptional situations or "outliers" in the macroprudential context. We have thoroughly described the nature of liquidity via an Abstraction Hierarchy. When the Risk Map system is implemented, we will be able to further examine the following:

- Whether leverage is country-specific or industry-specific. Leverage has implications for credit risk.
- Whether Companies with high leverage (in terms of total D/E) are more likely to become financially distressed than those with low leverage?
- Investigate whether macroeconomic shocks, such as the 9/11 terrorist attack, the 2008 financial crisis, the Greek debt, Brexit, or Covid-19 have an impact on leverage.

To test the usefulness of visual analytics in systemic risk modelling, more work is needed to examine how financial analysts make decisions, in particular, to identify decision-making logic and translate that into a decision support system for automated trading or portfolio management. This work paves the way for an IS design science research project that will generate knowledge about our proposed method for designing a decision support system (DSS) for liquidity risk management and the system's design.

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