An instance-based-learning simulation model to predict knowledge assets evolution involved in potential digital transformation projects

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Software engineering professionals need to consider which technological solution is appropriate to meet their client's needs as well as the impact of solutions on their organisation. However, the decision to implement a solution is not yet explicitly based on how it may empower the most important organisational assets: the knowledge assets. Organisational knowledge assets are the foundation of the knowledge economy, and a key element in evaluating the health of an organisation. This paper provides software engineers a simulation model which illustrates the decision-making process for the implementation of technological solution based on an evaluation of their client's knowledge assets and how such assets may impact and be impacted by the deployment of a specific technological solution. To do this, we use an agent-based approach, implementing an instance-based learning model (a cognitive approach) to represent scenarios for decisions based on experiences. A pool of 11 case studies was used to train the prediction engine and validate the usefulness of the simulation model in generating scenarios and nurturing decision-making and user experiences.

Keywords: digital business management; decision-making; knowledge assets management; decisions from experience; technology in the knowledge economy; digital business evolution

Introduction

Organizational decision-making must evolve as information and technology supporting it evolves as well. This paper presents an instance-based learning simulation model to visualize the evolution of organizational intangible assets involved in a potential digital transformation project, to make better decisions about to implement or not a specific digital transformation project given the intangible assets predicted evolution.

Digitalisation is accepted as the way business will keep competitive in the present and the future, but, deciding which digital project to implement, and why, is the challenge that we propose to overcome by predicting the evolution of the intangible assets of the organization to be digitised, and given this evolution, decide whether or not implementing a specific digital transformation project.

We propose to use a simulation model that takes as an entry a set of intangible assets characterised according to the SIPAC methodology (Sanchez-Segura, Medina-Dominguez, et al., 2016) (a brief explanation of this methodology will be given below), and from that initial scenario of the real state of the organisational intangible assets, predict how those intangible assets would evolve, so that, based on this evolution, how a potential digital transformation project could be affected can be predicted as well, letting decision-makers to better decide whether or not implementing a specific digital transformation project.

For building the simulation model in this work, an instance-based learning approach was used, which mimics the cognitive process of "learning based on experiences", for representing organizational learning based on historic decisions, that is, this model represents decision making regarding digitalization processes and emulates the potential outcomes based on previous experiences that enable the model to predict the expected behaviour of a set of knowledge assets after a digitalization strategy is set and implemented.

Considering this, we want to explore the following research question:

- Is it possible to emulate the cognitive process of deciding if implementing or not a technological solution, and why, based on the evolution of the organizational knowledge assets?

In the remainder of this section, we are going to explain what we understand by a competitive organization, why intangible assets are a lever to keep organizations competitive, and why the evolution of the status of organizational intangible assets are a key aspect to make decisions about implementing or not a specific digital transformation project.

Software and technology are now an essential part of many businesses, irrespective of the field in which they operate. Software and technology can be said to be at hand and everywhere. Software companies operate within a complex sector inundated with information and where little or nothing is entirely under control. The internet revolution, the rapid growth of computing properties, the changing landscape of software and technology and the changing needs of businesses have created a market in which only the most competitive can survive.

The term competitive can be understood as “the more a software and technology company sells the better”. In the knowledge and/or digital era, however, competitiveness is not about just selling, but rather about helping clients achieve their business goals using the appropriate software and technological solutions in a sustainable way.

To be competitive, software and technology providers must appreciate the importance of a client’s knowledge and organisational culture, of what sets the client apart from competitors and what the clients have learned to do, that is, their know-how. This knowledge, the key asset in company recognition, can be used to ascertain how successfully a client company is achieving their organisational goals. Company knowledge refers to the non-tangible resources that allow companies to deliver their value proposition (Marr, 2008). A company's success is not guaranteed merely by the financial (money, credit, etc.) or physical assets (computers, buildings, etc.) that support its operations (Sanchez-Segura, Ruiz-Robles, et al., 2017). The vital resource of a knowledge-intensive company is intellectual capital, that is, its intangible knowledge assets. Thus, a company with better intangible knowledge assets has better prospects for long-term success (Andrews & De Serres, 2012; Axtle-Ortiz, 2013; Greco et al., 2013; Khan, 2014).

The importance of considering knowledge assets as the key to developing solutions that meet a company's business needs is illustrated by listing some of the leading companies in terms of economic and future prospects: Google, Amazon, Facebook or Apple.

If we accept that business success increasingly depends on effective technological solutions, IT consultants and software engineers are more important than ever in helping companies achieve their business goals (by proposing appropriate software and technological solutions). Assuming this is the role of technology consultants or providers of software and technological solutions, what are the tools they use to demonstrate the potential impact of their proposed solutions for their clients? Currently, the assurances of experienced consultants or software engineers is deemed to be enough. But what if clients could visualise their near future and judge for themselves whether or not investing in a technological or software solution is worth it?

A simulation tool used by technology consultants or software engineers to support their proposed solutions to the real needs of clients would be a powerful tool for decision-making about the implementation of one or other software or technological solution. By visually demonstrating the evolution of a company's knowledge assets, such a tool would allow clients to understand how good the proposed solution is likely to be in achieving their business goals. This approach offers a new way to navigate the current knowledge economy in which success depends on making the right decisions on the technology or software solutions used to exploit knowledge assets.

The value of intangible assets in the software industry

A relatively new field of research has focused on the value of intangible assets in technology companies. The starting point was the development of a taxonomy for identifying organisational intangible process assets in two small software services companies (Ruiz-Robles, 2017; Sanchez-Segura, Medina-Dominguez, et al., 2016). This research led to the development of a methodology to help stakeholders evaluate the health of an organisation based on its organisational process assets. For this, researchers proposed a number of key indicators and analysis of process assets based on their impact on business goals (Sanchez-Segura, Ruiz-Robles, et al., 2017). Additionally, agent-based and system dynamics simulations were carried out (Sanchez-Segura, Dugarte-Peña, & Medina-Dominguez, 2018; Sanchez-Segura, Dugarte-Peña, Medina-Dominguez, et al., 2018). Researchers also proposed a biomimetic design of process assets based on concepts of natural intelligence and survivability, borrowing from swarm intelligence (intelligence of ant and honey-bee colonies) and identifying the features that both sets of process assets and individual process assets should have in order to operate intelligently and resiliently. Simulation modelling was used in this process (Sanchez-Segura, Dugarte-Peña, et al., 2017). This paper goes further, developing existing research by adopting the first decision-making model based on knowledge asset characterisation using simulation. This represents a paradigm shift. We are now developing a simulation model for use by software engineers as a decision-making tool for clients from any sector where technological solutions are required.

These solutions are based on the knowledge assets at the disposal of the client in the pursuit of its business goals.

Decision-making in software services

Two important references in software engineering are the guidelines Software Engineering Body of Knowledge (SWEBOK) and Project Management Body of Knowledge (PMBOK) (Bourque & Fairley, 2014; P.M.I., 2013). In this paper, we focus on the sections of SWEBOK and PMBOK dealing with the decision-making process for the services engineers offer their clients. However, decision-making is not a major subject of research in software engineering (Burge et al., 2008).

The SWEBOK is the reference par excellence on software requirements, design, construction, testing, maintenance, configuration, management, engineering processes, models and methods, quality, professional practice, economics, computing foundations, mathematical foundations and engineering foundations. The Software Economics section of SWEBOK states that it "covers the foundations, key terminology, basic concepts, and common practices of software engineering economics to indicate how decision-making in software engineering includes, or should include, a business perspective" (Bourque & Fairley, 2014). However, most research refer to value-based decisions in terms of software process costs, effort and estimation, while no in-depth research has been done into the complexities of decision-making. Decisions are made by human beings and must be addressed as a complex problem (Sanchez-Segura, Jordan-Goñi, et al., 2016).

From the perspective of software engineering, Burge and colleagues (Burge et al., 2008) focused on comprehending the decisions of software engineers as part of software engineering practice. They approach decision-making on a naturalistic basis (by humans) and how they can learn from considering the rationale as an output of human decision-making. However, an important point is that the trend has been to merely document the rationale for decisions rather than using it as a decision-making aid.

We focus on taking advantage of naturalistic decision-making in the software engineering context to dynamically represent the features of decision-maker learning by cognitively modelling their decisions.

Use of the instance-based learning (IBL) cognitive model for decision-making modelling

Prior research has explored the implementation of instance-based learning theory (IBLT) in order to improve explicitness, transparency and preciseness (Gonzalez, 2017; Gonzalez et al., 2003; Gonzalez & Dutt, 2011). Cog-IBLT was the first computational model based on IBLT, focussing on demonstrating various mechanisms and the learning process for a resource allocation problem (Gonzalez et al., 2003). This paper draws on a broader experimental cognitive architecture ACT-R (Anderson & Lebiere, 1998) to model the concepts of activation (a value that identifies the potential usefulness of an instance based on memory, experience and relevance to a current context and environmental constraints); partial matching (the representation of the similarity between instances), and retrieval probability (the probability of an instance being retrieved according to activation and partial matching). Likewise, Lebiere (Lebiere, 1998) presented the concept of blending (an aggregate of the values of multiple instances available in memory).

Once IBLT was established as a formal theory of cognition, a number of models were created for various instance-based problems, focusing on highly complex, dynamic tasks (i.e. training, the effect of fatigue, etc.) (Gonzalez, Best, et al., 2011; Gonzalez et al., 2015; Gonzalez & Dutt, 2010), tasks related to skills acquisition through simple stimulus-response and repeated binary-choice tasks (Lejarraga et al., 2012). Although it is a descendent of ACT-R (Lebiere, 1998), the IBL model is representative mainly of ACT-R declarative memory and was successfully tested in modelling competitions (Erev et al., 2010; Gonzalez, Dutt, et al., 2011; Gonzalez et al., 2013).

More recent uses of the IBL model and experience-based decision-making have primarily addressed distributed domains, ranging from decision-making models in energy-related interaction with buildings (von Grabe, 2017; von Grabe & González, 2016), studies in behavioural science on the effect of switch rates or optional stopping in choosing between options based on expected rewards (Soo & Rottman, 2018), or human decision-making in autonomous vehicles (Govindarajan & Bajcsy, 2017).

This paper analyses the use of the IBL model, using the NetLogo simulation tool, for a technological solution selection problem. The model and the learning mechanisms for decision-making are described in the Materials and Methods section below. The results of the use of the simulation model are presented in the Results section and the Discussion section analyses the accuracy of the model prediction compared to the real case. The final section offers conclusions and suggestions for future research.

Materials and methods

The most important decision in business technology or software is the choice of a solution from a number of technological alternatives. Simply put, the role of technology consultants and software engineers is to offer clients several alternatives to meet their business needs. In the software industry, before a software solution is deployed, the service provider (represented by the software engineer) is awarded a contract following business negotiations or a bidding process.

This study offers a simulation model that can be used by software engineers to show their clients the effect of proposed software solutions, thus facilitating the decision-making process. The aim of this model is to generate simulated scenarios to represent the client company's health which, in the knowledge economy, refers to a company's knowledge assets and their potential response to decisions on the implementation of a technological solutions.

As an entry to the predictive simulation model that we propose in this work, a client company's knowledge assets (also called intangible assets) must be assessed and measured. The SIPAC-maethodology (Systemic Intangible Process Assets Characterisation Framework) can be used to assess and measure the state of a company's intangible knowledge assets based on its intellectual capital (Sanchez-Segura, Medina-Dominguez, et al., 2016), (Dugarte-Peña, 2019) and evaluate the company performance in terms of its organisational knowledge. To do this, a company's intangible assets must be identified and categorised (Sanchez-Segura, Medina-Dominguez, et al., 2016), measured and characterised (Sanchez-Segura, Ruiz-Robles, et al., 2017), modelled and simulated using technological simulation software (Sanchez-Segura, Dugarte-Peña, et al., 2017; Sanchez-Segura, Dugarte-Peña, Medina-Dominguez, et al., 2018). Once the intangible assets have been characterized to reach a specific organization's business goal, this is the entry to the predictive simulation model. However, to date there has been little research into the decision-making process involving both the software engineer and the client company. This decision-making process and the simulation model will be explored in this paper.

We used a cognitive modelling approach (Anderson & Lebiere, 1998; Gonzalez et al., 2003), specifically, the instance-based learning (IBL) model (Gonzalez, 2013; Gonzalez et al., 2003; Lejarraga et al., 2012; von Grabe, 2017) to represent how humans make dynamic decisions and select from different alternatives based on their perceived utility and previous experience (decisions from experience). The NetLogo (Wilenski, 1999;

Wilensky, 2012) modelling and simulation tool was used to create the simulation model.

Assessing and Characterising the Knowledge Assets State

Before explaining the simulation model created, we are going to explain in this section, some details about how the entry to the simulation model is created.

The SIPAC-framework (Dugarte-Peña, 2019; Sanchez-Segura, Dugarte-Peña, et al., 2017; Sanchez-Segura, Dugarte-Peña, Medina-Dominguez, et al., 2018; Sanchez-Segura, Ruiz-Robles, et al., 2017) encompasses a general assessment and characterisation of:

- The achievement of a strategic goal
- The knowledge assets of a company

The achievement of a strategic goal is measured using the sum of the evaluation of all related knowledge assets and their importance in achieving the specific goal. A company's knowledge assets are measured using key indicators identifying the quality of the assets and their impact on the achievement of strategic goals.

Each knowledge asset is evaluated using one or several indicators that provide an overall assessment of the state of the asset. Similarly, a strategic goal may be assessed according to the various knowledge assets that may impact its achievement.

The process is as follows:

(1) Normalise and standardise indicators

(2) Assess Indicators individually

(3) Assess knowledge assets from their related indicator's performance

(4) Assess the achievement of strategic goals

For this model to work, the knowledge assets and key indicators must be identified. The SIPAC-framework uses an audit spreadsheet (Dugarte-Peña, 2019)for direct on-site data collection and the on-line tool available at http://spaengineering.sel.inf.uc3m.es/, for the collection, storage and retrieval of information of a company's strategic goals, knowledge assets and the corresponding indicators.

The information required to identify a company's knowledge assets is indicated in Table 1.

<<<<<<<<< Table 1 here >>>>>>>>>>

Just as knowledge assets are evaluated and given a weighting, indicators are also given a weighting depending on their impact on the assessment of a knowledge asset. For every indicator, a weight (WI_m^n) is assigned according to the contribution of indicator "n" to the performance of the knowledge asset "m". Table 2 shows the aspects to be identified and measured for each indicator of a knowledge asset. In general, these aspects describe the measurement criteria, differentiate an indicator from another, define whether they are representative of quality or impact, represent the importance of the indicator to the knowledge asset, and sets the boundaries within which the indicator may range.

<<<<<<<<< Table 2 here >>>>>>>>>>

Normalisation of Knowledge Asset Indicators

With the information provided in Table 2 for every indicator, a double transformation of the indicator's values is proposed in order to better combine the information and assess the indicators general performance:

(1) A standardisation of actual and target values that comprises the transformation of the original actual and desired values to a scale [0,1] independently of the real range values.

(2) A normalisation of every indicator that, from the standardised values generates a unique value representative of the state of health of the indicator.

Standardisation of indicators

The standardisation of actual and target values is given by the following equations and rules:

- If the value “Sense” of an indicator equals 1, (the higher the value, the better the performance), then the **standardised** value of the indicator is as given in Equation 1. The value can be -1 or 1, meaning "lower is better" or "higher is better" respectively. For example, we can define 2 indicators: "number of positive ratings" and "number of negative ratings"; clearly the higher the number of positive ratings the better (higher is better) and the lower number of negative ratings (lower is better):

$$X' = \frac{X - X_{MIN}}{X_{MAX} - X_{MIN}} * (1) \qquad (1)$$

Where X represents the actual or target value of the indicator, and X_{MIN} and X_{MAX} represent the minimum and maximum possible values, i.e. the possible range of the indicator.

- If the value “Sense” of an indicator equals -1, (the lower the value, the better the performance) then the standardised value of the indicator is given as:

$$X' = \frac{X - X_{MAX}}{X_{MAX} - X_{MIN}} * (-1) \qquad (2)$$

When all indicators are standardised, they will all be in a range [0,1], independently of their value, so they can all be compared as similar from a quantitative point of view.

Normalisation of indicators

As mentioned above, in addition to standardising the actual and target values of indicators, this work proposes a normalisation which, based on the actual and target value, computes the normalised value of the indicator, that is, the state of health of the indicator. This normalisation is given by Equation 3 and Equation 4.

- If the value "Sense" of an indicator equals 1, (the higher the value, the better the performance), the normalised value of the indicator is given as:

$$X_{NORM} = \frac{X'_{Act} - X'_{Target}}{X'_{Target}} \qquad (3)$$

- If the value of an indicator equals -1, (the lower the value, the better the performance) then the normalised value of the indicator is given as:

$$X_{NORM} = \frac{X'_{Act} - X'_{Target}}{X'_{Act}} \qquad (4)$$

Where X_{NORM} is the normalised value to calculate, X'_{Act} is the previously standardised actual value, and X'_{Target} is the previously standardised target value. This value ranges generally from – 1 to 1, although there may be cases of values overshooting or undershooting the limits of this interval. These are still valid and merely indicate values scoring higher or lower than the established interval limits[1].

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[1] For example, an indicator may have a reference interval of [5,20]. However, in some cases, an indicator may have values higher than 20 or lower than 5, which would result in standardised values higher than 1 or lower than -1.

- A colour scale was created to illustrate these normalised values of the indicators, with upper and lower thresholds of the corresponding colour, Figure 1.

<<<<<<<<< Figure 1 here >>>>>>>>>>

Using this colour scale, it is easy to identify which indicators are in a poor (red), acceptable (orange) and good state (green). The state of the indicator is identified by the thresholds, determined by the client company and captured and applied by the IT/SW professional.

Assessment of Knowledge Assets

This consists in using the standardised-normalised indicators to assess knowledge assets. This assessment involves the generation of a quantitative value indicating the general state of health of the asset using Equation 5:

$$KA_{VAL}^{n} = \sum_{i=1}^{m} WI_i^n * X_{NORM}^{i} \qquad (5)$$

Where KA_{VAL}^{n} is the valuation of the knowledge asset “n”, which has “m” indicators, and with every normalised indicator X_{NORM}^{i} assigned a weighting representative of its importance of WI_i^n.

Quantitative Assessment of a Strategic Goal

The quantitative assessment of a strategic goal consists in taking all the individual valuations of the knowledge assets and calculating the state of achievement using Equation 6.

$$SG_{VAL} = \sum_{k=1}^{n} W_k * KA_{VAL}^{k} \qquad (6)$$

The quantitative valuation of a strategic goal (SG_{VAL}) is the sum of the valuations of each knowledge asset, multiplied by their corresponding weighting.

Quantitative Impact Assessment

The impact of a knowledge asset is evaluated by taking into consideration the normalised indicators classified as “impact” indicators. The subset of impact indicators, given a set of “p” normalised impact indicators for a knowledge asset “n”, is evaluated using Equation 7:

$$\boldsymbol{I_{VAL}^{n}} = \frac{\sum_{i=1}^{p} X_i^n}{p} \qquad (7)$$

Where X_i^n is each of the ***p*** normalised impact indicators of the knowledge asset ***n***.

Quantitative Quality Assessment

As with the impact valuation, the quality valuation considers only the indicators of the ***quality*** of a knowledge asset. The subset of quality indicators, given a set of ***q*** impact indicators for a knowledge asset ***n***, is evaluated using Equation 8.

$$\boldsymbol{Q_{VAL}^{n}} = \frac{\sum_{i=1}^{q} X_i^n}{q} \qquad (8)$$

Where X_i^n is each of the ***q*** normalised quality indicators of the knowledge asset ***n***.

The principal difference between these three valuations (general, impact or quality) is that the general weighting provides a quantitative value representing the state of the asset, regardless of whether this asset affects the impact on achieving strategic goals or related quality, but rather focusses on the overall importance of the indicators, whereas the impact and quality valuations are specific to these aspects regardless of weighting. This will be useful for the characterisation described in the following sub-section.

Characterisation model for Knowledge Assets

The characterisation of every knowledge asset in this methodology is based on the initial proposal by Sanchez-Segura (Sanchez-Segura, Dugarte-Peña, et al., 2017; Sanchez-Segura, Dugarte-Peña, Medina-Dominguez, et al., 2018; Sanchez-Segura, Ruiz-Robles, et al., 2017). This was expanded to include not only knowledge assets with both impact and quality, but those only of impact and only quality. This opens for consideration a wider range of possibilities for impact and quality combinations, all important in real organisational contexts.

Knowledge Assets may be characterised in terms of their impact on a business goal and their quality as organisational assets. There are three cases for characterising knowledge assets based on the type of indicator:

- Case 1: Knowledge assets with both impact and quality indicators (Warning, Replaceable, Evolving or Stable).
- Case 2: Knowledge assets with only quality indicators (Acceptable or Unacceptable).
- Case 3: Knowledge assets with only impact indicators (Acceptable or Unacceptable).

These three cases are shown in Figure 2, case 1 in a grey frame, case 2 in yellow and case 3 in pink.

<<<<<<<<< Figure 2 here >>>>>>>>>>

As shown in Figure 2, there are several coloured quadrants representative of “states” that constitute the different levels of characterisation. The black segmented lines dividing the quadrants are the thresholds of impact and quality at which these may be considered acceptable or not.

The characterisation thresholds define the values at which the quality and impact valuations switch from a bad or worse to a good or better and acceptable situation. In other words, these thresholds are barriers established by companies to define the performance goals for the quality and impact of their knowledge assets.

There are eight possible states of characterization, grouped in three possible categories:

With both Impact (I) and Quality (Q) indicators:

These are assets containing indicators measuring both the impact on the strategic goal achievement and the quality of the asset itself. There are four characterization states in this category:

- Warning Asset: Located in the red section of Figure 2, these assets are considered to be in a bad state since they do not overcome the stablished quality and impact thresholds. These assets must be carefully watched since they are threatens to the assets ecosystem and are having a negative general impact in organizational behavior, so important decisions about rescission or replacement must be made.
- Replaceable Asset: Located in the orange section of Figure 2, these assets have good quality (more than the threshold) however the impact is not enough (less than the threshold). This means that these assets are worth to be replaced by assets with the same purpose but with a higher impact.
- Evolving Asset: Located in the blue section of Figure 2, these assets have good impact (more than the threshold) however the quality is not enough (less than the threshold). This means that these are assets worth of receiving investment for improvement.
- Stable Asset: Located in the green section of Figure 2, these assets have both good quality (more than the threshold) and impact (more than the threshold). It means that they are relevant and are supporting positively the strategic goal achievement.

With only Impact (I) indicators:

- Unacceptable Impact Asset: Located in the lower left side section, these assets are based only on impact indicators. For them, the impact measure does not overcome the threshold, which means that their effect on the system's behavior is not enough significant.

- Acceptable Impact Asset: Located in the upper left side section, these assets are based only on impact indicators. For them, the impact measure overcomes the threshold, which means that their effect on the system's behavior is significant.

With only Quality (Q) indicators:

- Unacceptable Quality Asset: Located in the left lower side section, these assets are based only on quality indicators. For them, the quality measure does not overcome the threshold, which means that their effect on the system's behavior is negative, so must improve.
- Acceptable Quality Asset: Located in the right lower side section, these assets are based only on quality indicators. For them, the quality measure overcomes the threshold, which means that their effect on the system's behavior is positive and are valuable.

The re-characterisation of Knowledge Assets as a cognitive learning mimicking approach

Since a knowledge asset is characterised at a determined moment, it is possible they can be in a different state at another moment. This is the case with knowledge assets that may be characterised in an audit as in one state but in a future audit be characterised in another state. This may be due to changes in organisational policy or a consequence of decisions made.

As noted above, there are eight possible characterisations of knowledge assets.

However, the following conditions must be considered:

- A KA with both impact and quality indicators (Case 1) may be characterised as Warning, Replaceable, Evolving or Stable.
- A KA with only impact indicators (Case 2) may be characterised as Acceptable Impact Asset or Unacceptable Impact Asset.

- A KA with only quality indicators (Case 3) may be characterised as Acceptable Quality Asset or Unacceptable Quality Asset.

The transition matrixes and state diagrams for these possible KA states can be represented as follows:

Table 3 shows all transition matrixes for the Markovian process of KA characterisation. By definition, there are three clearly distinguishable cases possible: both impact and quality, only impact and only quality knowledge assets. The table shows the probabilities of transitions, while the others are shown as “-”.

<<<<<<<<< Table 3 here >>>>>>>>>>

The corresponding state diagram for the previous matrix is shown in Figure 3. There are 8 possible states for a knowledge asset and the possible transitions are shown with black arrows.

As it may be assumed, the characterisations are mutually exclusive, i.e. a knowledge asset may correspond to only one of these three cases, which is why the probability matrix only shows valid probabilities within each of the cases, while the other spaces remain disabled.

<<<<<<<<< Figure 3 here >>>>>>>>>>

In order to discover the real probability values of the transitional matrix, an experience-based training was proposed, taking advantage of the information available from companies (case studies) that have used the SIPAC-framework and implemented the suggested digital solution.

This matrix is generated by exploring each of the audits and identifying the probability of knowledge assets to be re-characterised when the first and second audits are compared. Figure 4 illustrates the process of exploring the cases available and updating the probability matrix.

<<<<<<<<< Figure 4 here >>>>>>>>>>

For every knowledge asset, the previous characterisation is identified as *i*, and the subsequent characterisation is identified as *j*; this identification corresponds to the ID column of Table 4. In order to obtain the probability matrix, first an occurrence matrix must be obtained by exploring the previous and subsequent characterisation states of every knowledge asset.

<<<<<<<<< Table 4 here >>>>>>>>>>

From this, the occurrence (Occ_i^j) of a transition is defined as the number of times in which knowledge assets switch from the previous *i* state to the subsequent *j* state. The whole set of possible transitions is presented in Table 5.

<<<<<<<<< Table 5 here >>>>>>>>>>

From this the probability matrix can be broken down. For the re-characterisation probability matrix estimation to make sense, some restrictions must be considered:

- Type 1 (both impact and quality) knowledge assets can only be characterised as 1, 2, 3 or 4.
- There is a considerable number of case studies $= \mathrm{n}_1 + \mathrm{n}_2 + \mathrm{n}_1 + \cdots + \mathrm{n}_\mathrm{n}$, each with a determined k_n number of knowledge assets, summing up $\mathrm{k} = \mathrm{k}_1 + \mathrm{k}_2 + \cdots + \mathrm{k}_\mathrm{n}$.
- The total number of knowledge assets considering the total cases for training, corresponds to the total number of transitions of the occurrence matrix, so:
- $k = \sum_{i=1}^{8} \sum_{j=1}^{8} Occ_i^j$
- For each case study we have two audits: previous and subsequent to the implementation of the suggested digital solution.

Given ***n*** number of case studies, and for the occurrence matrix given before, for each known previous ***i*** state, the probability of transition to the ***j*** state is given by Equation 9.

$$p_i^j = \frac{Occ_i^j}{\sum Occ_i} \qquad (9)$$

The previous probability equation and the considered restrictions to the type of knowledge asset, quality or impact, allows us to determine the transitional probability matrix for the model of re-characterisation of knowledge assets, as shown in Table 6.

<<<<<<<<< Table 6 here >>>>>>>>>>

From the previous matrix, it can be said that a given knowledge asset previously characterised as i can only be re-characterised as:

- $\{1|2|3|4\}\ if\ (i = 1|2|3|4)$ [i.e. the case of both quality and impact]
- $\{5|6\}\ if\ (i = 5|6)$ [i.e. the case of only quality]
- $\{7|8\}\ if\ (i = 7|8)$ [i.e. the case of only impact]

Instances of IBL-model implementation: learning from experimentation as in cognition

The instances definition

The IBL (instance-based learning) model (Lejarraga et al., 2012) focuses on characterising the learning of dynamic tasks through instances stored in a "memory" representing the experience of decision making events. The instances considered in the dynamic decision-making process of the SIPAC-framework refer to the digital solution selection and are the trio defined to represent the memory of an expert "decision-maker" in the context of the implementation of a digital solution through the deployment of the SIPAC-framework. According to the IBL model, instances are composed of a situation "S", a decision "D" and an obtained utility "U". We describe the instances of the experience-based software solution selection problem below, emulating the process of decision-making with regard to the selection of a digital solution within an organisational context.

The specific combination of Situation-Decision-Utility for the software selection problem is shown in Table 7.

<<<<<<<<< Table 7 here >>>>>>>>>>

Situation (S): In dynamic decision-making, according to the IBL model, the situation of an instance is defined by all the elements that describe a subsystem state any time a decision is made. These could be regarded as state variables that describe the subsystem at a given time and distinguish it from the subsystem state at another point in time. For the problem at hand, *situation* in the proposed model means a pair of states for each knowledge asset, a preceding one and a subsequent one. The KA state is determined by the characterisation of knowledge assets described above and based on the work of Sanchez-Segura et al. (Sanchez-Segura, Dugarte-Peña, et al., 2017; Sanchez-Segura, Ruiz-Robles, et al., 2017), which may characterise each knowledge asset as evolving, stable, warning, replaceable, acceptable/unacceptable of only quality KA and acceptable/unacceptable of only impact KA. Since there are eight possible characterisation states for the knowledge assets and two transitional states (pre and post decision), a total of 4^2(type 1)+2^2(type 2)+2^2(type 3)=24 pairs of states are used to define the possible situations of these instances as the transition between two of these eight possible states, taking into consideration that knowledge assets of both quality and impact have four possible states, while only impact or only quality knowledge assets have two possible states (see Table 7, above). For example, the *situation* of an instance could be the transition of a knowledge asset from *Evolving* to *Stable* after a decision is made.

Decisions (D): The decision to be considered in this model is the selection of one of two alternatives: (A) Implement a technological solution suggested by the IT/SW professional as the best alternative to achieve the client's business goal based on client know-how, or (B) Do not implement any change (see column 3 of Table 7). These decisions can be regarded as experience-based decisions (Gonzalez, 2013), since the decision-maker will discover the outcomes and their probabilities while addressing the stated problem with abstract tools and models, such as simulations.

The IBL model is open to considering more than two decisions. As far as we are concerned here, it makes more sense to consider the real options open to the client company when it has to make a decision to meet its needs: whether or not to accept the IT/SW professional's knowledge-based proposal.

The decision made will result in significant and far-reaching changes to the client company, since big decisions entail big responsibilities. Irrespective of the decision made on whether or not to implement the technological solution, knowledge assets can mutate. Consequently, the state of the company's knowledge assets can, according to this model, change, leading to a chain reaction within the company. Accordingly, the company can, for example, be more sustainable (among other benefits) the better the state of the knowledge assets. It is not currently possible to predict the evolution of a company with respect to a change in the state of its knowledge assets. Therefore, the aim of the proposed model is to predict the impact of the implementation of a software or technological solution proposed by a software engineer on the state of the client company's knowledge assets.

Utility (U): Generally speaking, utility (U) can, according to the IBL model, be regarded as the outcome of making a decision D in the situation S. For the digital solution selection problem, utility is determined by the difference between the revenue of a business case in the previous audit and the revenue in the subsequent audit, i.e., given the previous (I_p) and subsequent (I_s) revenues of a company, the utility (U) of its related instances is defined by Equation 10.

$$\boldsymbol{U} = \Delta \boldsymbol{I} = \frac{\boldsymbol{100} * \boldsymbol{I_s}}{\boldsymbol{I_p}} - \boldsymbol{I_p} \qquad (10)$$

The decision-maker is for determining which decision to make, i.e., the chief information officer, the chief executive officer, the IT director, etc. Company success is reflected in the characterisation of its knowledge assets: a good decision will result in better knowledge assets, and a bad decision will not lead to changes or will degrade knowledge assets. Ultimately, this will have a direct impact on organisational profit. In this model, utility is defined as the difference (as a percentage) of a company's revenue, explained by Equation 9, resulting from strategic decisions and how these impact each knowledge asset and, ultimately, company profits.

For the decision-maker, this instance-based learning model the utility is expected to represent the effect of decisions, which is why good decisions are expected to generate a positive higher utility (reward), and bad decisions are expected to generate a poor or even negative utility (punishment).

Assuming that several case studies used the SIPAC-framework, a generic utility matrix can be obtained, similar to the occurrence or probability matrixes previously presented. This generic utility matrix is an estimation of the effectiveness of the SIPAC-framework in improving organisational knowledge assets from the implementation of digital solutions specifically aligned with strategic goals. Table 8 illustrates the generic utility matrix; which will be more precise the more cases that are used.

<<<<<<<<< Table 8 here >>>>>>>>>>

According to Table 8, the utility for a knowledge asset previously characterised as *evolving* and subsequently characterised as *stable* is $R_{E\text{-}S}$ should correspond to a specific variation in a company's revenue; however, it may be representative of other forms of utility that can be measured and compared, thus enabling the generation of a difference, or ΔI.

$$\text{If } CH_t = E \text{ and } CH_{t+1} = S\text{, then } R(Evolving \rightarrow Stable) = R_{E-S}.$$

Let us suppose, for example, that a knowledge asset has been characterised as *evolving* and is re-characterised as *stable* as a result of the decision to implement technological solution X, and the revenue variation between before and after the decision is 120%. The instance could be defined as:

- Situation (S) = Evolving→Stable
- Decision (D) = Implement technological solution X
- Utility (U)= 20.

Re-characterisation of Knowledge Assets as a learning-based process according to the IBL-model

In this proposal, the technology selection decision-making process is conceived as a dynamic process from the perspective of the Instance Based Learning theory, shown in Figure 5.

The IBL-model has been widely used to represent several types of decisions, as noted in the introduction, but we have used it to represent the dynamics of a very different kind of decisions: strategic decisions with regard to digital solution implementation. While frequently used to represent trivial decisions, our research proposes to mimic these cognitive processes, aiming to design a method to explore and evaluate choices before making decisions, first using a simulated model but finally using real decision making.

<<<<<<<<< Figure 5 here >>>>>>>>>>

This process of decision-making using the IBL-model is best understood by explaining the subprocesses of the decision-making learning process implicit in the implementation shown in Figure 5 above, based on instances with trios of information about experiences including a situation (S), a related decision (D) and the utility obtained (U).

Recognition

Experience-based decisions in any field depend on repeated decisions, trial and error. This can be extremely expensive and unaffordable in a technological context given that the implementations of software and digital solutions is expensive. Generally, only highly paid consultants, consultancy firms and very skilled decision-makers have the experience required to choose between technological solutions. When tens of thousands or even millions of euros are at stake, a talented decision-maker with experience in making similar risky decisions and achieved good outcomes will be required to make the choice between two or more alternatives. Therefore, it is necessary to account for previous experiences in the choice of digital solutions. These experiences represent *instances,* including information on decisions made under similar conditions; instances that are used when needed as a result of an expert ability to connect and correlate situations and variables by similarities.

The instances refer to or contain information on how decisions on technological solutions have been made in the past but are not easily accessible. Decision-making based on this is potentially very useful but based on a paradigm that we believe should evolve towards a decision-making approach that is closer to the client’s reality, that is, more clearly linked with the client’s business needs.

We propose a perspective shift with respect to how software engineers make decisions about the most suitable technological solution for a client. Clients have business goals and are very aware that achieving these will guarantee survival. Any action taken by the company, including of course, the choice of technological options, must be based on the client's business goals and know-how. This leads to the question of how a software engineer can demonstrate that the proposed solution is aligned with the client's business goals. The purpose of the model proposed here is to provide the client with evidence of why the proposed solution aligns with both its know-how and its business goals.

Based on memories of decisions and situations producing company know-how and business goal alignment, recognition is represented in this simulation model by the characterisation of knowledge assets. Simulation modelling will explore all possibilities and create memories that are impossible to investigate in real life, building a set of references that can be queried when a new decision has to be made and an experienced opinion is required.

Judgement

Judgement involves evaluating the expected utility of alternatives based on experience or heuristics (Gonzalez, 2017). This decision-making model will judge between alternatives based on simulated experiences that previously explored the alternatives and their related situations, decisions and utility.

Experienced decision-makers routinely do this intuitively when they look to memory and experience to compare environments, special conditions and user needs. The process activates memories to recall what the results (outcomes) of each alternative would be. Our model implements this cognitive subprocess by storing and comparing simulated instances (experiences) that represent the decision-maker's memories previous results of the alternatives at hand. For each pair of alternatives, this model uses a *blending* mechanism to estimate which option is best. Given that each instance will be associated with one of two decisions, and each of the instances has an associated utility, the *dominant* (higher) average utility will define the blended value for each of the decisions. This will determine the best of the two alternatives.

For example, the state of a company's knowledge assets (warning, evolving, replaceable or stable) may have changed as a consequence of simulated decisions. In the hypothetical scenario that a company's knowledge asset switched from warning to stable as a consequence of implementing a software or technological solution, the company's defined utility is expected to be very good. It will, in any case, be better than for the again hypothetical scenario in which another technological solution for the same company failed to change the state of the knowledge asset from warning or slightly improved its state to replaceable.

Choice

The act of choice consists of selecting the best alternative based on the above judgement. Thanks to the judgement subprocess, the decision maker can create a criterion for selection based on the expected utility, i.e., the highest blended value. The simulated model compares the results based on experiences with all of the alternatives under evaluation (two in our case, see column 2 of 8). It then selects the alternative decision that is expected to yield the best possible outcome as the best choice. In this model, the decision criterion is denoted by the blended value, an IBL model artefact that calculates a value for each of the choices as a function of activation and results.

Execution

The execution subprocess is the implementation of the selected decision, or, in other words, the implementation of the technological solution that the model considers best to satisfy the client's needs. In industry, technological solutions are deployed with or without the intervention of the expert. Large companies have their own personnel with experience in deploying technological solutions who receive dynamic feedback and supervision. In small- and medium-sized companies, however, the consulting role is mostly performed by an expert who is paid an hourly rate for evaluating the situation, advising on decision making and providing feedback after implementation. Execution in this simulated model is determined by the company's knowledge asset transition probabilities.

Good or bad decision-making on software solutions would, in real life, entail high financial and performance risks that not every company can afford. Through simulation modelling, however, a company can experiment without risk, while gaining valuable knowledge that will support decision-making and provide a general understanding of company dynamics.

The effect of implementing a solution at a client company will be represented by the re-characterisation of intangible assets as a result of solution. This in turn depends on the pre-calibrated probabilities of transition determined for each client organisation, i.e., a company with a better maturity level will be more likely to re-characterise its knowledge assets after the deployment of an appropriate software solution.

Feedback

The feedback subprocess consists of updating the utility of an instance according to its activation based on several experiences. Although the transition will be determined by a transition probability matrix, there is little probability of counterintuitive selection in simulation modelling. Accordingly, the model can fully explore all the possibilities and update the utility based on the better choices.

The learning mechanism is implemented in any IBL model through a feedback loop. If the model is to be truly dynamic, a learning process should be enacted for each of the experiences. In this model, after an experience has been *gained*, the related instance stored in memory is updated. Formally, feedback entails selecting the instances to be reinforced and the rate of reinforcement of the utility of these instances (Gonzalez, 2013).

In this model, the activation parameter of an instance agent, and its expected utility, is updated as part of the feedback. The pool of instances available for comparison at the time of the memory query is then updated to give a clear picture of the best and worst instances. The model thus chooses the alternative that would produce the best outcome. Since the decision-making process is simulated repeatedly, the impact of recognising and updating the instances as representative of better and worse rewards is very useful for both the software engineer (who can demonstrate the benefits of good decision-making, increasing the probabilities of winning a contract) and the client (who can foresee the benefits to the company).

Implementation of learning mechanisms through simulation models

As part of this decision-making process, there are several mechanisms enabling the learning process, including the Smart Decision-Making Module.

The learning mechanisms represented in this model were presented firstly as part of the ACT-R cognitive architecture, and secondly as part of the IBL model. The most representative mechanisms are described below.

Pre-population

In view of the complexity of these situations, involving a transition between states, all the options need to be considered to begin with. For this, a pre-population of agents (instances) is initially deployed. The pre-population process consists in creating all possible decision-making instances. For this, all the pre and post characterisation states should be considered. Given that there are 4^4 possible transitions between before (PRE) and after (POST) characterisation and two possible decisions (N_D), the number of initial instances will be determined as follows:

Number of initial instances:

$$N = N_D * PRE^{POST} = 2 * 4^4 = 32\ instances.$$

Blending

The blending mechanism is inspired by *blending* as proposed by Lebiere (Lebiere, 1999). It is used to assess the attractiveness of different alternatives based on previous outcomes. Given that the simulation model is used to carry out several experiments, instances saved in memory contain attributes that can be used to compare the alternatives. In the particular case of the software selection problem, the comparison is carried out as a selection model based on the blended values calculated for each of the choices. In previous experiences, all the choice options and outcomes will have been saved as instances. The best option will represent the decision (A or B) with the greatest expected utility (reward) based on previous experiences.

Results: use of the simulation model

The framework suggests the use of a simulation model in two stages: first, using a module that automatically characterises knowledge assets in a graphical agents-based interface; and second, using a module aimed at representing the predicted impact of the SIPAC-framework proposal may have on knowledge assets (See Figure 6). This evolution is based on an IBL-model representation of dynamic decisions. Both simulation modules become an input for decisions to be made in the real organisational context.

<<<<<<<<< Figure 6 here >>>>>>>>>>

Module for visualising the entry to the simulation model: characterised Knowledge Assets

By using this agents-based model, the IT/SW professional can automatically represent and visualise the previously characterised knowledge assets of a company. To do so, the model handler (i.e., the IT/SW professional or company management) has several alternatives:

- To select from preloaded cases a specific case characterisation.
- To upload a csv file with information of a new case and characterise its knowledge assets.

The model handler can also set the impact and quality thresholds that define the characterisation, that is, the values of standardised quality and impact valuations, so that the characterisation may be more or less flexible within the thresholds.

It is important to note that this characterisation has been described as “static” since it represents the state of knowledge assets at the time the previous audit. This following strategic questions may be considered:

- How would the knowledge assets be characterised if they were in a better state?
- How would they be re-characterised if we decision-makers were more flexible (configuring lower impact and quality thresholds) or more demanding (higher impact and quality thresholds).
- What does it mean that most of knowledge assets are characterised as stable or warning.
- What assets do we need to focus on to improve the impact on strategic goals?
- What assets are in the best state, to be used as levers or inputs for improvement?

The control panel for visualisation of the characterisation, shown in Figure 7 (left), allows the IT/SW professional to visualise the previously characterised knowledge assets of a client company. This control panel guides the IT/SW professional through four general steps to characterise knowledge assets:

- Step 1: Reset stored information and load data
- Step 2: Data loading mode selection and operation
- Step 3: Simulation World Configuration
- Step 4: Knowledge Assets Characterisation

Figure 7 (right) shows the simulated world in which the knowledge assets will coexist and be characterised according to their impact and quality. As shown, the characterisation is given by the area in which the knowledge assets are located in a determined moment. At this point, the characterisation is static, that is, represents the real values of indicators of every knowledge asset.

<<<<<<<<< Figure 7 here >>>>>>>>>>

The second module of the simulation model is used to provide a dynamic representation of the evolution of knowledge assets,

Module for learning-based prediction of the evolution of Knowledge Assets

This work integrates an application of the IBL-model since it was appropriate for representing the difficult task of exploring alternatives and comparing them based in their outcomes. Additionally, the whole learning process of the IBL-model (a strong theoretical model) was used since it represents the way that cognitive memory works, providing this work with an approach for representing smart decision making, as is shown in the following section.

This module allows the evolution of a company's knowledge assets to be predicted using the information of previous cases as a general reference. Essentially, this simulation model trains instances through trials, following these steps:

- **Recognises** the instances associated to the business case under study (Recognition of the IBL-model).
- **Judges** between two alternatives, i.e., it explores what has occurred in the past with knowledge assets with similar characterisation states when the digital solution was implemented (Judgement of the IBL-model).
- **Makes a choice**, guided by the best expected utility for each alternative (Choice of the IBL-model).
- **Re-characterises** (as a prediction) the knowledge assets, using the probabilities obtained from the real previous cases experimentation (Execution of the IBL-model).
- **Updates the information** of the instances (situation, decision and utility) with the obtained re-characterisation information (Feedback of the IBL-model).

An example of how the prediction looks is shown in Figure 8. Instances related to decision A (Implementing a digital solution) are represented as black circles, while instances related to decision B (not implementing a digital solution) are represented with beige circles. The approximation of the instances represents the usefulness and occurrence of each instance, i.e. instances which are closer have been used more often and represent a higher utility value. The blended value represents the merit of the alternative choice. In this case, the blended value of decision A is higher than the blended value of decision B, thus, A would be the best decision.

<<<<<<<<< Figure 8 here >>>>>>>>>>

Apart from the best predicted decision, this model shows the dynamic re-characterisation for each trial. In Figure 8, assets 1 and 5, initially characterised as Warning are re-characterised as Stable. Knowledge Assets 2, 3 and 4 moved from Warning to Replaceable. Asset 6 remained unchanged.

Training from real cases data

The experience implementing digital solutions and the effect of these on knowledge assets was measured using real case studies from 11 small and medium enterprises. The companies belonged to different sectors but all had a common need: to improve their business performance through a digitalisation strategy or solution.

Organisational knowledge, know-how itself, is complex. In this experiment, it was possible to work with small and medium organisations, which were more likely to share their experiences and showed more interest in knowledge-based improvements to become more competitive with minimum risks. The complete list is shown in Table 9.

<<<<<<<<< Table 9 here >>>>>>>>>>

These cases were used to train the model, since for every company there were two knowledge audits: one initial with the base information of knowledge assets, and one performed after the implementation of the digital solution. This information was used to generate the Matrix of Probabilities for Knowledge Asset Transition from one state to another, used in the re-characterisation of assets in the simulation model.

Brief description of the real case used for validation

In this research, we used information from an organization to test the accuracy of the simulation model at predicting the behaviour of the knowledge assets after the implementation of a digitisation strategy. The selected organization (name hidden attending nondisclosure agreement directions) is a public institution with the goals of:

- Creation of multidisciplinary scientific teams that generate knowledge appropriate to the complexity of the problems related to the safety of motor vehicles.
- Dissemination of the work carried out by the affiliated research teams.
- Formation of scientifically based opinion in relation to the lines of research and technological development.
- Creation of a channel of communication and exchange of opinion between specialists in the lines of research of the institution with other institutions related to the automotive sector.

This is a small institution with 50-60 workers. These have varied professional profiles: senior and junior researchers, technicians, administrative assistants, interns, students and visiting researchers. Among the services provided it can be mentioned:

- Auditing and evaluation of risks and safety in the automotive field.

- Developing collaborative knowledge related to risk prevention and safety culture in the automotive field.

- Setting policies for continuous improvement of risk prevention in the automotive sector.

After the first knowledge assets assessment, and as a result of such assessment, the digital strategy proposed and implemented in this institution was the "Implementation of an open-source web platform containing a cloud-based knowledge repository, a knowledge-sharing incentivization module and a private/public interface for web diffusion”. The next sections explore the results and quality of the prediction made.

At the moment of publishing this research, a third audit was being deployed to evaluate the long-term success of the implemented solution, which will probably redound in future policy changes and the proposal of new and updated technological solutions more appropriate for the expectedly evolved current knowledge assets.

Knowledge Assets evolution prediction

The main use of the simulation model is to estimate how knowledge assets may evolve as a result of decisions for the implementation of technological solutions. An example taken from a real case prediction is provided below. Figure 9 shows three specific views of the simulation window: First, the characterisation of the knowledge assets in the initial audit; Second, the prediction of the simulation model based on previous real cases. Third, the real characterisation of the knowledge assets in the second audit (after the implementation of the digital solution).

<<<<<<<<< Figure 9 here >>>>>>>>>>

It is important to take advantage of the simulation model to improve decision making. By comparing the previous figure’s characterisations, it is possible to have an idea of the accuracy of the simulation engine, since we can compare the prediction with the real characterisation made after the implementation of a solution. The accuracy of these predictions is discussed below.

Discussion: on the accuracy in a real case

Figure 10 shows the predicted and real characterisation of a knowledge asset before and after the implementation of the digital solution. As can be seen, in five out of seven cases the prediction was correct.

To test the efficacy of the simulation, the prediction must be compared with the real results of the characterization for this specific case.

As it may be seen, in most of the characterizations of knowledge assets obtained (5 out of 7), the prediction coincided with the real characterization. Specifically, knowledge assets identified as 2, 3, 4, 5 and 6 are recharacterised exactly as suggested by the simulation model.

In the case of knowledge asset 1, the prediction failed, since it expected this asset to be recharacterized as “Stable” but it only achieved an “Evolving” state. This may be explained by the insufficient improvement in the quality assessment for such an asset. There was a significant improvement in such quality, going from -0.2 to 0.1, however, this improvement needed to achieve a value higher than the defined quality threshold (0.15) to be characterized as “Stable”, so with the current conditions the re-characterization was not possible.

However, the discussion is possible about how far the original quality valuation was, and the significant improvement achieved, which remains to be a good indicator for the effectiveness of the SIPAC-framework’s suggested solution, which was the simulated scenario.

In the case of the knowledge asset identified as 7, the simulation predicted improvement in both the quality and the impact valuations, so that it was expected to be re-characterized as Stable. However, the real re-characterization showed such an asset as Replaceable, with no change in characterization state. This may be explained by the extremely bad state of the initial impact valuation that the knowledge asset had before the implementation. The initial impact valuation was -0.36, which is far from the established impact threshold of 0.1. Although there was an improvement in such impact, going from -0.36 to 0.03, this improvement was not enough to overcome the threshold which was established at 0.1, however, as in the previous case, the effectivity of the SIPAC-framework may be discussed, given that the improvement occurred.

In cases where the prediction was not correct this was due to the configuration of the simulation model itself. In the first prediction failure, the corresponding knowledge asset was originally evolving. As such, it needed to improve on quality to become stable. Although quality improved, -0.2 before implementation and 0.1 after, this improvement was not enough for a re-characterisation of the asset. Given that the quality threshold was set at 0.15, improvement needed to be at least 0.35 and only reached 0.3; this, while insufficient, was not necessarily a poor outcome. It may be supposed that over time this asset may become stable.

<<<<<<<<< Figure 10 here >>>>>>>>>>

There was a similar occurrence with the other asset which was not re-characterised as predicted. The improvement was expected to be at least 0.46 to overcome the impact threshold (set at 0.1); although it improved from -0,36 to 0,03, this was not enough for re-characterisation.

Conclusions and future work

Digital technologies are now an essential part of our world, and the digitalisation of modern organisations is not merely a trend but rather a critical need to succeed in a global world of increasingly complex and dynamic environments for which traditional decision-making techniques is inadequate.

This paper offers an additional input to the limited set of tools and approaches that software engineers and business management have to support decision-making in selecting a technology solution or digitalisation strategy.

Beyond providing a visual tool for improved decision-making, this work presents a cognitive model that mimics the way that organisations learn from experience to improve decision-making. Specifically, this proposal implements a process of *learning* based on decisions on the implementation of technological solutions, using a simulated cognitive approach to evaluate alternatives rather than using the traditional methods based on reputation or cost, and focusing on real success in previous cases, even when the best alternative was to reject the proposed technological solution.

Through the development and use of the proposed simulation model, we were capable of emulating the process of deciding to implement or not a digitalization strategy based on previous experiences and using this expertise to project and predict the potential outcomes of the digitalization process.

For the professionals, the impartial judgement the model provides is crucial. The simulator is able to evaluate the experience of different companies providing technological services, and on this basis (previous services and experience) measure and assess past performance and so predict the success of a new endeavour in designing a digital strategy or proposed technological solution.

Finally, it should be noted that this work is valuable not only in the field of software engineering but also in cognitive modelling more broadly, expanding the scope of application by bringing its theoretical conception, the IBL (Instance-based Learning) model. It offers a useful and transparent user-centred application for learning with many advantages for final users who can make decisions based on experience without putting at risk what is most important: the client’s business success.

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Declaration of interest statement

The authors declare that there is no conflict of interest regarding the publication of this article.

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Tables

Table 1. Information of Knowledge Assets used in the assessment model.

Short-ID	Extended-ID	Description
KA-Name	The name of the Knowledge Asset.	This should be a short and representative name of the knowledge asset.
IC-type	Type of Intellectual capital.	This type of intellectual capital must correspond to the classification of (Marr, 2008).
KA-type	Type of knowledge asset.	This type of generic knowledge asset corresponds to the classification presented in section Materials and Methods section.
N-Ind	Number of indicators	This is the number of indicators that a specific knowledge asset has.
KA-weight	Weight of the knowledge asset	This is the weight (importance) that the knowledge asset has for the organisational strategic goal achievement.

Table 2. Elements of a Knowledge Assets Indicator.

Short-ID	Extended-ID	Description
Name	The name of the indicator.	This should be a short and representative name
Type	The type of indicator	It must take two possible values: (1) the indicator is of Quality type, and (2) the indicator is of Impact type.
Min_Val	Minimum possible value	This is the lowest possible value of the indicator. In other words, it is the lower limit of the interval of possible values.
Max_Val	Maximum possible value	This is the highest possible value of the indicator. In other words, it is the higher limit of the interval of possible values.
Sense	Sense of goodness	This represents the desired direction of the indicator. If higher values are better, it takes a value of 1, and if lower values are better it takes a value of -1.
Act-Val	Actual value of the indicator	This represents the current state of the indicator, i.e. it is a value higher or equal to Min_Val and lower or equal to Max_Val. In other words, it is the measure of the indicator in the present time.
Target_Val	Target value of the indicator	This represents the desired state of the indicator, i.e. it is a value higher or equal to Min_Val and lower or equal to Max_Val, but representative of a better state (if possible) than the Act_Val. In other words, it is the desired measure of the indicator in the future.
Ind-Weight	The weight (importance) for the knowledge asset.	This represents the importance of the indicator regarding the knowledge asset. The higher this value, the more important it is. (Note: importance is distributed among all the indicators of the asset; all weights of indicators of a same knowledge asset must total 1)

Table 3. Markovian transition matrix.

Transition probabilities		Stable	Evolving	Replaceable	Warning	Unacceptable Quality Asset	Acceptable Quality Asset	Unacceptable Impact Asset	Acceptable Impact Asset	Σ
		Post								
Pre	***Stable***	P11	P12	P13	P14	-	-	-	-	1
	Evolving	P21	P22	P23	P24	-	-	-	-	1
	Replaceable	P31	P32	P33	P34	-	-	-	-	1
	Warning	P41	P42	P43	P44	-	-	-	-	1
	Unacceptable Quality Asset	-	-	-	-	P55	P56	-	-	1
	Acceptable Quality Asset	-	-	-	-	P65	P66	-	-	1
	Unacceptable Impact Asset	-	-	-	-	-	-	P77	P78	1
	Acceptable Impact Asset	-	-	-	-	-	-	P87	P88	1

Table 4. Identification of characterisation cases.

ID	Case	Characterisation
1	1	Stable
2	1	Evolving
3	1	Replaceable
4	1	Warning
5	2	Unacceptable Quality Asset
6	2	Acceptable Quality Asset
7	3	Unacceptable Impact Asset
8	3	Acceptable Impact Asset

Table 5. Occurrence matrix from training.

		Subsequent Characterisation State								
		1	2	3	4	5	6	7	8	$\sum Occ_i$
Previous Characterisation State	1	Occ_1^1	Occ_1^2	Occ_1^3	Occ_1^4	0	0	0	0	$\sum Occ_1$
	2	Occ_2^1	Occ_2^2	Occ_2^3	Occ_2^4	0	0	0	0	$\sum Occ_2$
	3	Occ_3^1	Occ_3^2	Occ_3^3	Occ_3^4	0	0	0	0	$\sum Occ_3$
	4	Occ_4^1	Occ_4^2	Occ_4^3	Occ_4^4	0	0	0	0	$\sum Occ_4$
	5	0	0	0	0	Occ_5^5	Occ_5^6	0	0	$\sum Occ_5$
	6	0	0	0	0	Occ_6^5	Occ_6^6	0	0	$\sum Occ_6$
	7	0	0	0	0	0	0	Occ_7^7	Occ_7^8	$\sum Occ_7$
	8	0	0	0	0	0	0	Occ_8^7	Occ_8^8	$\sum Occ_8$
		$\sum Occ^1$	$\sum Occ^2$	$\sum Occ^3$	$\sum Occ^4$	$\sum Occ^5$	$\sum Occ^6$	$\sum Occ^7$	$\sum Occ^8$	$\sum_{i=1}^{8}\sum_{j=1}^{8} Occ_i^j$

Table 6. Transitional probability matrix.

<table>
<tr><td colspan="2"></td><td colspan="8">Subsequent Characterisation State</td><td></td></tr>
<tr><td rowspan="9">Previous Characterisation State</td><td></td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>$\sum p_i$</td></tr>
<tr><td>1</td><td>p_1^1</td><td>p_1^2</td><td>p_1^3</td><td>p_1^4</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>2</td><td>p_2^1</td><td>p_2^2</td><td>p_2^3</td><td>p_2^4</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>3</td><td>p_3^1</td><td>p_3^2</td><td>p_3^3</td><td>p_3^4</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>4</td><td>p_4^1</td><td>p_4^2</td><td>p_4^3</td><td>p_4^4</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>5</td><td>0</td><td>0</td><td>0</td><td>0</td><td>p_5^5</td><td>p_5^6</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>6</td><td>0</td><td>0</td><td>0</td><td>0</td><td>p_6^5</td><td>p_6^6</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>7</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>p_7^7</td><td>p_7^8</td><td>1</td></tr>
<tr><td>8</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>p_8^7</td><td>p_8^8</td><td>1</td></tr>
</table>

Table 7. Structure of an instance: situation, decision and utility.

<table>
<tr><th rowspan="3"></th><th colspan="3">Instances</th></tr>
<tr><th>Situation (S)</th><th>Decision (D)</th><th>Utility (U)</th></tr>
<tr><th>Transition from the “PRE” characterisation state to the “POST” characterisation state
PRE→POST</th><th>Decision to be made by the decision maker in the given situation (S)</th><th>Percentage revenue variation from the first to the second audit: after making the decision (D) in the situation (S)</th></tr>
<tr><td rowspan="16">Type 1: both impact and quality</td><td>Warning→ Warning</td><td rowspan="24">A: Implement a specific technological solution aligned with the client’s business goal and supported by client know-how

B: Do not implement any change at the company</td><td rowspan="24">% Revenue Variation</td></tr>
<tr><td>Warning→ Evolving</td></tr>
<tr><td>Warning→ Replaceable</td></tr>
<tr><td>Warning→ Stable</td></tr>
<tr><td>Evolving → Warning</td></tr>
<tr><td>Evolving → Evolving</td></tr>
<tr><td>Evolving → Replaceable</td></tr>
<tr><td>Evolving → Stable</td></tr>
<tr><td>Replaceable → Warning</td></tr>
<tr><td>Replaceable → Evolving</td></tr>
<tr><td>Replaceable → Replaceable</td></tr>
<tr><td>Replaceable → Stable</td></tr>
<tr><td>Stable → Warning</td></tr>
<tr><td>Stable → Evolving</td></tr>
<tr><td>Stable → Replaceable</td></tr>
<tr><td>Stable → Stable</td></tr>
<tr><td rowspan="4">Type 2: only quality</td><td>Unacceptable Quality Asset → Unacceptable Quality Asset</td></tr>
<tr><td>Unacceptable Quality Asset → Acceptable Quality Asset</td></tr>
<tr><td>Acceptable Quality Asset → Unacceptable Quality Asset</td></tr>
<tr><td>Acceptable Quality Asset → Acceptable Quality Asset</td></tr>
<tr><td rowspan="4">Type 3: only impact</td><td>Unacceptable Impact Asset → Unacceptable Impact Asset</td></tr>
<tr><td>Unacceptable Impact Asset → Acceptable Impact Asset</td></tr>
<tr><td>Acceptable Impact Asset → Unacceptable Impact Asset</td></tr>
<tr><td>Acceptable Impact Asset → Acceptable Impact Asset</td></tr>
</table>

Table 8. Reward/Punishment (utility) for knowledge assets characterisation transition.

		Post-decision state (t+1)							
		Stable (S)	Evolving (E)	Replaceable (R)	Warning (W)	Acceptable Quality Asset	Unacceptable Quality Asset	Acceptable Impact Asset	Unacceptable Impact Asset
Pre-decision state (t)	Stable (S)	R_{S-S}	R_{S-E}	R_{S-R}	R_{S-W}	--	--	--	--
	Evolving (E)	R_{E-S}	R_{E-E}	R_{E-R}	R_{E-W}	--	--	--	--
	Replaceable (R)	R_{R-S}	R_{R-E}	R_{R-R}	R_{R-W}	--	--	--	--
	Warning (W)	R_{W-S}	R_{W-E}	R_{W-R}	R_{W-W}	--	--	--	--
	Acceptable Quality Asset	--	--	--	--	R_{AQ-AQ}	R_{AQ-UQ}	--	--
	Unacceptable Quality Asset	--	--	--	--	R_{UQ-AQ}	R_{UQ-UQ}	--	--
	Acceptable Impact Asset	--	--	--	--	--	--	R_{AI-AI}	R_{AI-UI}
	Unacceptable Impact Asset	--	--	--	--	--	--	R_{UI-AI}	R_{UI-UI}

Table 9. List of companies used for training and validation.

ID	Company	Ambit	Location
A	ISVA- Duque de Santomauro Institute for Vehicle Safety	Innovation, Research and Development	Spain
B	EXA.PE	Software development	Peru
C	ETIPS.CL	Software development	Chile
D	VicMicro S.L.	Technological and Digital services	Spain
E	Tejados Ruiz S.L.	Construction	Spain
F	Grochel-MARKETING Soluciones Constructivas S.L.	Construction	Spain
G	Grochel-FORMATION Soluciones Constructivas S.L.	Construction	Spain
H	Pymeconsult	Professional services	Spain
I	Gráficas Mafra, S.L.	Graphic Art	Spain
J	CERAMA, S.L.	Construction	Spain
K	URIX	Construction	Spain

Figures

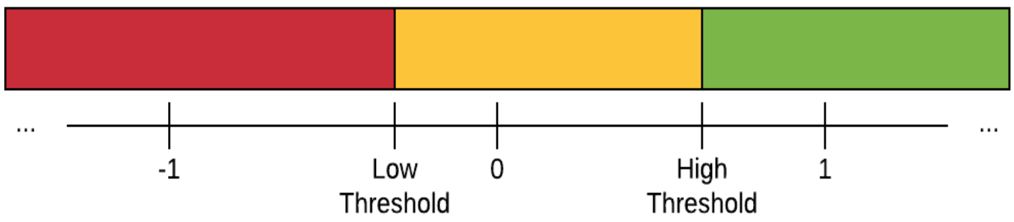

Figure 1. Colour of standardised KA indicators from the low and high thresholds.

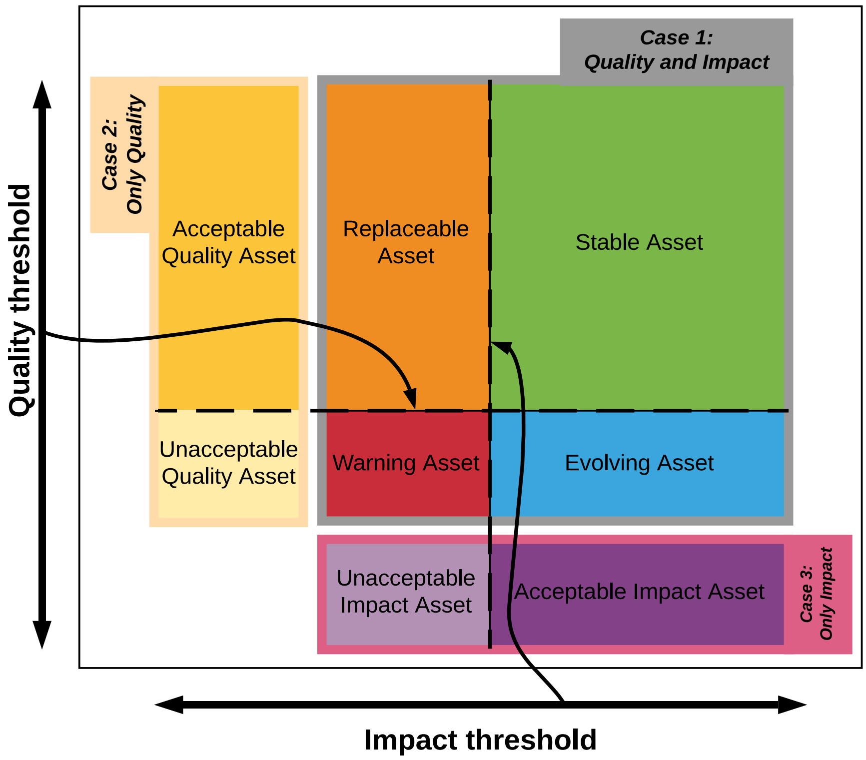

Figure 2. Extended characterisation of Knowledge Assets.

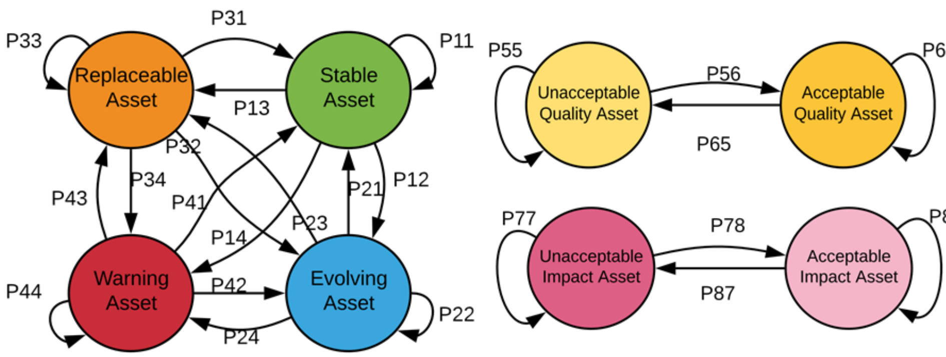

Figure 3. Full state diagram for the KA characterisation transitions.

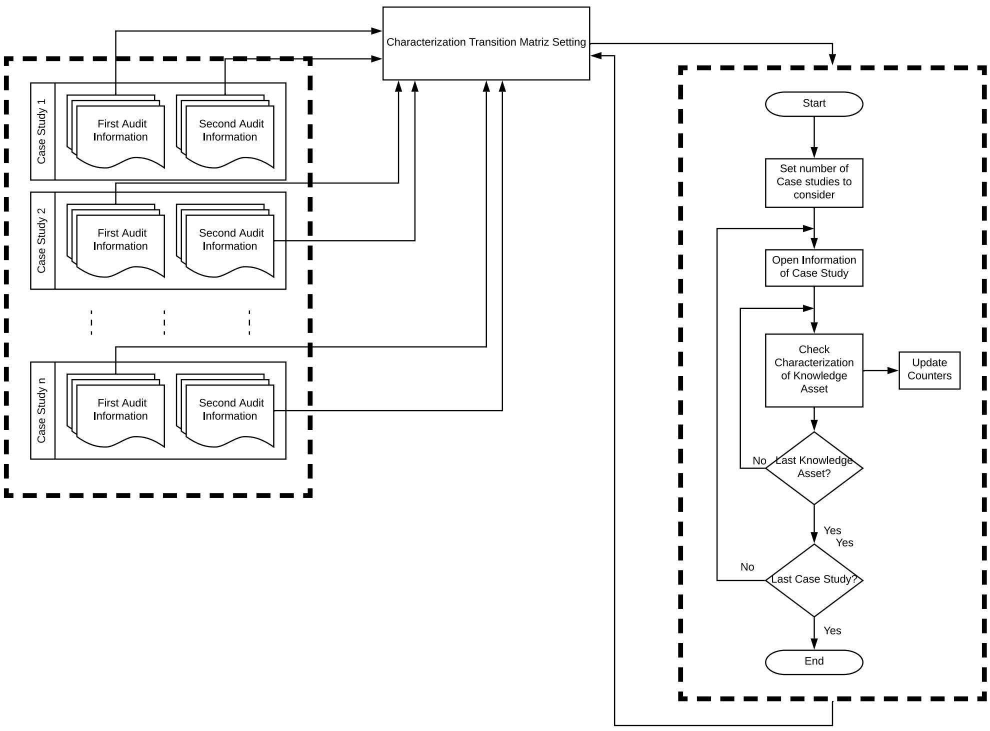

Figure 4. Probabilities of re-characterisation generation.

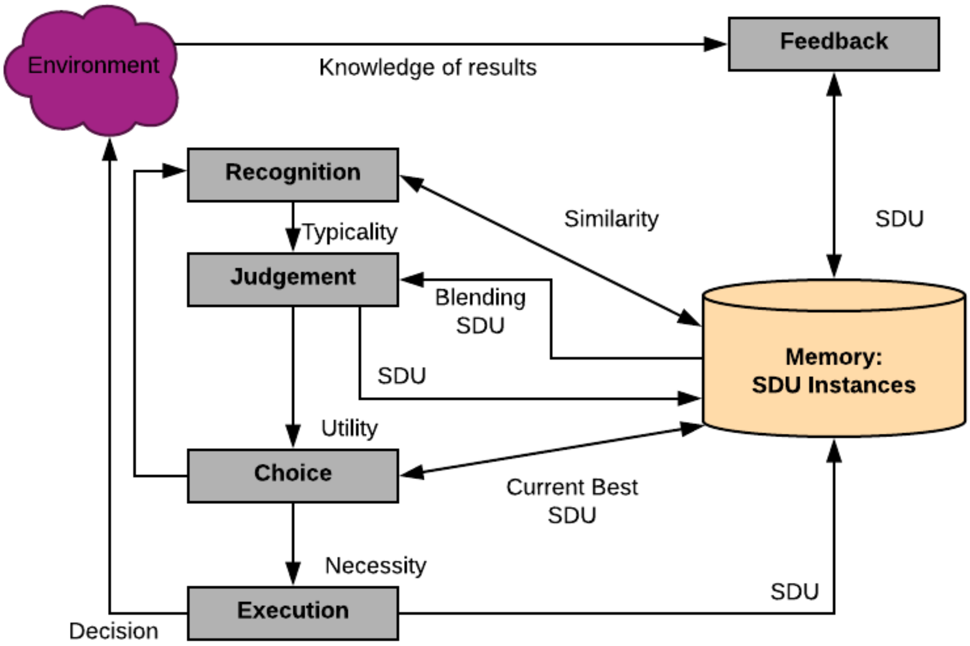

Figure 5. The IBLT process.

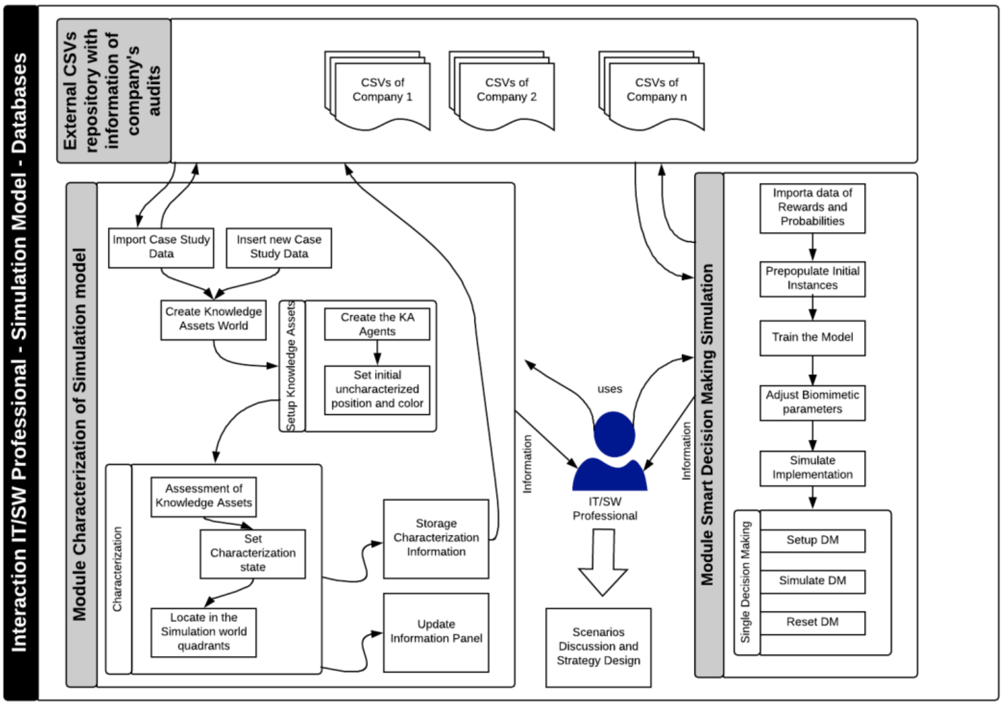

Figure 6. Interaction with the simulation modules.

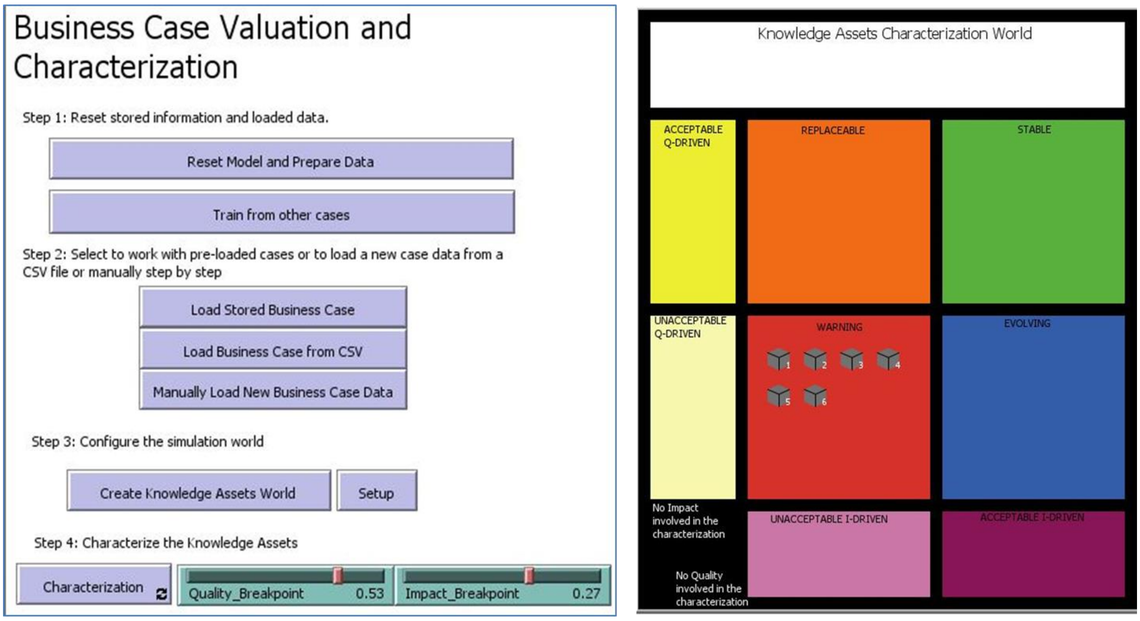

Figure 7. Configuration panel and characterisation world.

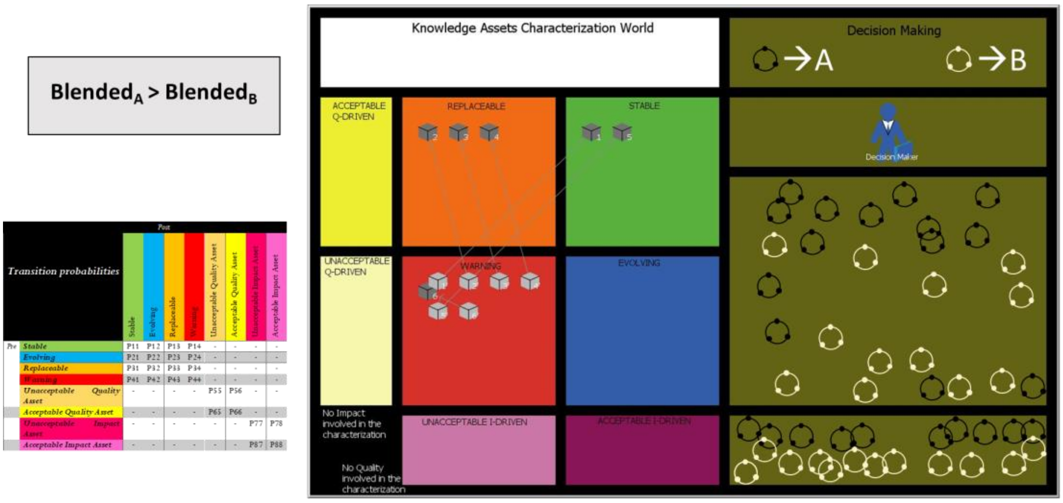

Figure 8. Simulation of evolution of knowledge assets and instances.

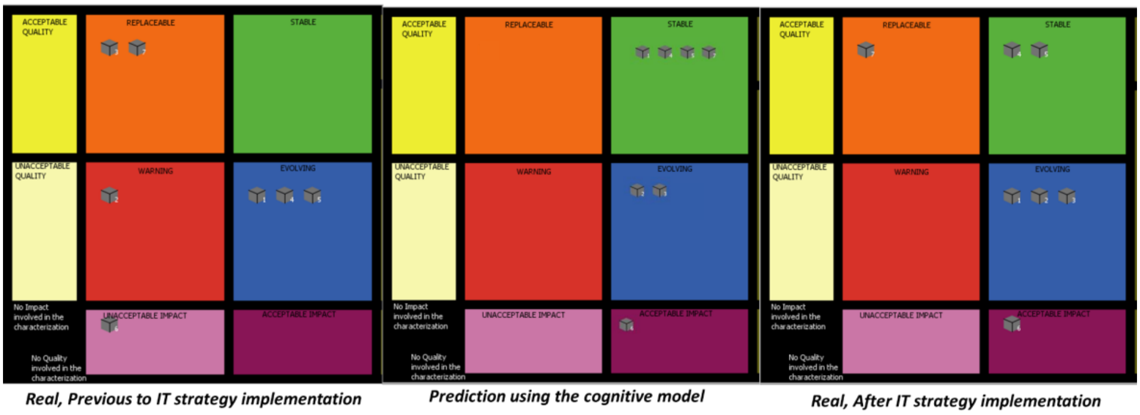

Figure 9. Estimation vs. Prediction using the simulation model.

			Impact Threshlod	Quality Threshold				
			0.1	0.15				
Digital Solution: Implementation of an open source web platform containing a cloud based knowledge repository, a knowledge sharing incentivation module and a private/public interface for web difussion.								
Real Pre-Implementation			Estimation using SIPAC-framework			Real Post-Implementation		
I-value	Q-value	Characterization	I-value	Q-value	Characterization	I-value	Q-value	Characterization
0.16	-0.2	Evolving	0.22	0.15	Stable	0.21	0.1	Evolving
-0.4	-0.1	Warning	0.21	0.1	Evolving	0.12	0.14	Evolving
-0.1	0.3	Replaceable	0.15	0.1	Evolving	0.18	0.12	Evolving
0.29	0.1	Evolving	0.23	0.25	Stable	0.18	0.21	Stable
0.3	-0.35	Evolving	0.215	0.2	Stable	0.32	0.18	Stable
-0.4	--	Unacceptable Impact	0.2	--	Acceptable Impact	0.32	--	Acceptable Impact
-0.36	0.18	Replaceable	0.12	0.21	Stable	0.03	0.23	Replaceable

Figure 10. Accuracy of the simulation model, by knowledge asset.