Concept of an agent-based simulation of the spread of quantum computer-safe encryption measures

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Abstract

Quantum computers are currently in development. Because they are expected to be able to crack many encryption measures used today, quantum computer-safe encryption measures need to be spread between market participants to keep them safe. Especially small and medium enterprises can be vulnerable in this regard. Because there is not enough historical data available to use most data-based prediction models, an agent-based simulation model concept is proposed to explore the possible future diffusion process between companies in the market and test different influencing factors for their relevance to find out which combination of factors can be seen as beneficial to this diffusion. With companies acting as agents, central elements of an agent-based simulation model concept based on internal (employees, management, general internal knowledge, and resources) and external (customers, government, other companies) influencing factors are created. Simulation scenarios are conceived to explore different possibilities of the spread of quantum computer-safe encryption measures between agents, like the diffusion being influenced by the government, a few big companies, or multiple smaller companies. In future research projects, this model concept will be realised, and the simulation scenario runs will be carried out. Based on the information gained during these explorative simulation runs, important influences could be identified and later used to support the adoption of quantum computer-safe encryption measures between all market participants.

Keywords: ABM; quantum computing; diffusion

1. Introduction

Quantum computers are currently in development and expected to supersede classical computers in specialized tasks (also called “quantum supremacy”) (Arute et al., 2019; Preskill, 2019). Because of their increased computing power, they are expected to be helpful in many industries. However, they can also pose dangers because of it – by breaking encryption that before the advent of quantum computers was considered safe (Mailloux et al., 2016; Sharma & Ketti Ramachandran, 2021). Because preparation is necessary to implement quantum computer safe measures and attackers can store encrypted data now and encrypt it when quantum computers are available for more widespread use (a so-called “store-now-decrypt-later attack”), many companies can already be considered late in their security preparations (Joseph et al., 2022). The quick implementation of new quantum computer-safe encryption measures as soon as they are available will be necessary because of this. These urgently needed measures are not yet available in their finalized form (NIST, 2022) and will need to be distributed quickly between all market participants on availability because of this.

While all market participants will need to be protected from this new threat, especially small and medium enterprises (SMEs) can be expected to need additional support in the implementation phase as they can be considered especially vulnerable to IT security incidents (Schindler & Ruhland, 2022b). As a vital part of the economy (European Commission, 2020), their safety is of great importance. Research is needed to understand how new technologies, especially quantum computer safe measures, can best spread between SMEs and other market participants as soon as they are available to reach everybody in time, and support the companies that need it during adoption. Knowledge about the most important influencing factors can help support this spread and could later be used to support relevant market participants during it.

To be able to predict and evaluate this diffusion process in the market in a possible future scenario, a model needs to be created, as similar diffusion processes of that scope have not been thoroughly documented and modelled yet. However, as exact historical data is unavailable, classical prediction models that need existing data to create predictions and trends cannot be used (Montesinos López et al., 2022). Since evaluable amounts of statistical data on the behaviour of market participants on the spread of countermeasures on behalf of an innovation of this scope are unavailable, other means must be used to gain insights. A simulation with variable input data can alleviate this problem. Additionally, this has the benefit of being able to discover yet unknown network effects or interactions occurring within the context of macroeconomics or microeconomics and exploring different scenarios. This way, exploration can be done to find out which market participants and circumstances have the most influence on the diffusion of adoption and which scenario or combination of scenarios improves the spread of quantum computer-safe measures in the market.

This paper aims to establish a concept that can be used in further research to conduct an agent-based simulation for the diffusion of quantum computer-safe measures in the market. Based on this simulation, the knowledge gained could be used to infer measures to help SMEs with the process of acquiring this new technology faster or easier.

2. The concept of an agent-based model (ABM) for simulations

The challenge in this specific situation is a lack of data and similar trends to extrapolate the potential growth. An additional hurdle is also the necessary consideration for social interactions and the behaviour of people and organizations. These greatly influence the diffusion and transition dynamics for the adoption and usage of technologies. Simulating the transition under these circumstances proves to be highly complex because of the influence of a broad range of contextual factors (Edmonds & Moss, 2013).

Recent studies in the literature regarding a prediction model for the adoption of other technologies have already addressed the above-mentioned issues by using an ABM framework (Haringa, 2010; Kiesling et al., 2012; Zhao et al., 2011). Agent-based modelling is a complex approach that avoids reductionist assumptions and allows for more interdependency, a wider range of uncertainty and more diversity. It provides an intuitive modelling framework to consider the distinct characteristics of both human behaviour and technology (Taylor et al., 2016). The usage of ABMs to support policy decision-making is slowly increasing and examples of ABMs to tackle "real world" problems can be found, even though they are not a mainstream method in university science departments (Taylor et al., 2016). An alternative could be regression models or closely related approaches to extrapolate growth based on past trends (Nikolic & Ghorbani, 2011), a widely used approach in policy decision-making.

Some of the more prominent benefits shown by ABMs over other modelling techniques are observation of emergent phenomena, natural description of an often-complex system, and high flexibility. Especially the ability to capture emergent phenomena is of utmost importance. These are the result of the interactions of independent acting entities or "agents" (Bonabeau, 2002). Agents can exhibit certain behaviours like learning new information, adapting to the environment or new situations, and interacting as well as influencing other agents around them. Through these heterogeneous interactions, agents can generate network effects which in turn may lead to significant deviations from envisioned aggregate behaviour. Depending on an individual's behaviour that needs to be described, the computational complexity increases exponentially as the complexity of the behaviour increases (Bossaerts & Murawski, 2017). A more natural way to describe a system would be with the help of activities rather than fixed processes (Bonabeau, 2002). In regard to adopting new technologies, it is important to understand consumer behavioural patterns to guarantee the effectiveness of future policies (Sommerfeld et al., 2017). Because of the multitude of factors influencing an organization to switch to innovative encryption technology, ABM techniques provide a suitable framework to simulate the adoption decision process of the members of a heterogeneous social system (Stavrakas et al., 2019). The framework is based on members' individual preferences, behavioural rules, and communication within a social network (Macal & North, 2010; Ringler et al., 2016). To act in their best interest, agents need a form of rationality. A rational agent can be defined as such based on the choices of the agent in regard to the actions taken to optimize its outcome with respect to these preferences (van der Hoek, 2003). When agents must evaluate their next action based on the rules provided and other environmental factors, problems can arise. This is especially prominent in a fast-changing system where the agent is confronted with a best new option each moment and there is no time between planning an action and being able to execute it before picking a new plan of action. The notion of intention will be introduced to limit each agent's time needed to decide on their next action. Based on this notion, agents will only consider actions that are aligned with their current intention. This reduces the range of available options for the agent and thus shortens the time needed to make a decision (Rao & George, 1995). For the implementation of a rational agent, the belief-desire-intention (BDI) model will be considered. It is based on a widely respected theory of ration actions and behaviours in humans (Bratman, 1999). Intuitively, an agent's beliefs represent the informational state of the agent: everything the individual agent knows about the world and other agents around it. These beliefs may be incomplete or incorrect and are open to future changes. An agent's desires represent the motivational state. They are a set of circumstances that the agent would, in an ideal world, wish to be brought about. And lastly, an agent's intentions represent a deliberate state of desires that it has committed to achieving (Cohen & Levesque, 1990).

To realize the simulation, formulas and variables need to be conceptualized for the specific use case.

3. Modelling the market

Roger's diffusion theory offers insights into integral components of the diffusion process: the innovation itself (in this case quantum computer-safe encryption technologies), the communication channels between agents that can spread information (because awareness of the innovation is needed), the social system that exists around the agents (that can influence their adoption decision) and the passing time. (Rogers, 2003). Companies in the market are under the influence of several external and internal factors that can shape their behaviour. While the customers, the government and other companies can be classified as external factors that can influence an agent, internal factors include the company's employees, management and general internally available knowledge (Schindler & Ruhland, 2022a). Based on this structure, variables for the agents in the simulation can be created. In the context of this simulation, companies (e.g. bigger companies, SME or the providers of standardized software solutions) and organisations (e.g. the government or research institutes) can act as agents. The individual internal and external influences that companies face and how these could be implemented in an ABM are explained in tables 1 and 2. In the following, central elements for the decision-making of agents during an agent-based simulation for the diffusion of quantum computer-safe encryption measures between companies in the market are proposed. These can be used to create a simulation model during later research.

Table 1: Internal factors and their operationalization

Internal factors	
Employees	Employees mainly can influence the adoption with their availability of or lack of knowledge regarding the technology, supporting or hindering it.
	employees (driving force for adoption) = $emp = [-1, 1]$
Management	The management as decision-makers in the company has a strong influence on the technology adoption strategies of a company, shaping its course with their decisions, either using their knowledge and experience to drive the adoption forward or hinder it with their lack thereof.

	management (driving force for adoption) = $man = [-1, 1]$
General internal knowledge & resources	The general internal knowledge and resources of a company can shape the possible expanse of an adoption, the level of training that would be necessary to adopt and if external help is needed for that purpose. The more internal knowledge of the subject of adoption or the more resources are available, the easier the adoption and vice versa. Funds are defined by the resources available for adoption plus the governmental financial support. Each year the internal resources will be increased to reflect additional assets or new employees being assigned to or hired for the adoption project.
	internal knowledge (is new technology known) = $in_{know} = [0, 1]$ internal resources (resources for adoption available) = $in_{res} = [0,1]$ funds available (reserve assets that increase yearly and financial influence by the government) $= funds = in_{res} * \left[\left(\frac{av}{12}\right)\right] + gov_{fin}$

Table 2: External factors and their operationalization

External factors	
Customers	Customers mainly act with their demands in the market and their intention to buy. Their demand or ignorance of quantum computer-safe technologies in the market can influence the importance a company places on that technology to meet customer interests.
	Customers will not be modelled inside the simulation their pressure will be represented by an individual specific factor, $pre_{cus} = [0, 1]$, to indicate how important they are to each agent.
Government	The government can influence the decision of a company to adopt a new technology by supporting it (e.g. financial incentives, regulatory support that reduces uncertainties) or hindering it (e.g. legal barriers, institutional unpreparedness). Financial and legal influence can be exerted that way.
	government financial (penalties and subsidies) = $gov_{fin} = [-1, 1]$ government legal (legal barriers and laws) = $gov_{leg} = [-1, 1]$
Other companies	Other companies act as an additional influencing factor. They can either support an agent by sharing knowledge and resources or forming partnerships in the market, or act as competition that increases the scarcity of available technology or puts pressure on a company to adopt. Because other companies are represented by agents, a social link will be implemented to reflect their relationship.
	communication (social link) = $com = \frac{1}{k} \sum_{i=0}^{k} sl(i)$ market pressure = $pre_{mar} = \frac{1}{n} \sum_{i=0}^{n} adopt(i)$

The BDI model itself does not define any possibilities for communication and exchange of information between agents (Guerra-Hernández et al., 2004). However, communication between companies in the market needs to be reflected in the model as it is an integral part of not only Roger's diffusion theory in general (Rogers, 2003), but also the established influencing factors. To establish communication in the model, the authors propose to implement a combination of "social graph" and "social link". The "social graph" will be used to determine which agents know about each other and can (based on that knowledge) interact. This interaction can also be used to check the technology adoption status ($adopt = [0,1]$) of other agents. An increase in the adoption of the new technology will lead to a higher pressure to action on the agent. The "social link" will simulate the social relationship between the agents that can communicate based on the graph (Svennevig, 2000; Taillandier et al., 2019). This can be implemented as an asymmetric six-digit tuple representing the identification of the agent concerned by the link; followed by degrees of $liking = [-1,1]$, $dominance = [-1,1]$, $solidarity = [0,1]$, $familiarity = [0,1]$, and $trust = [-1,1]$. With the help of this concept, a complex relationship, and the degree of interactions between individuals can be simulated. A strong social link offers the connected agents a greater influence on each other. A positive social link can indicate a good relationship or reliability (e.g. for a state agency, a mother company or partnership), while a negative social link can be an indicator of mistrust or unfamiliarity (e.g. competing, or new companies). A social link between two agents is not necessarily symmetric in nature and can be positive for agent A to B and negative for B towards A. The social link will therefore determine the quality of the information being shared between agents and how the agent will react to it.

During the simulations, a global event will be triggered which will represent the introduction of the new technology to the agents. This moment of availability ($av = [-\infty, \infty]$) can also be used to slowly increase internal resources available to organisations. This will reflect assets being reserved or new personnel being assigned or hired for corresponding projects.

Inertia is introduced into the model (Eq. 1 and 2) to decrease the speed of decision making by the agents in the simulation (Young, 2009). While there are multiple possible reasons for a delay of diffusion in the market, the simplest reasons are internal barriers in companies like challenges in production, implementation, or a general delay in adapting to the new circumstance. Inertia will be set to an arbitrarily chosen value of reasonable size and kept throughout all simulations within a test scenario to not further influence differences between them. This value that must be decreased by each agent individually slows down the simulation if a high number is set, as agents will have to reach this value to decide to adopt. This also allows to set different speeds for inertia during special scenarios (like for technology interested companies that react faster). During the simulation, inertia is reduced each iteration according to the set formula. If inertia falls below a certain previously set value (like for example zero), agents can start to choose to adopt the new technology. If inertia is still over the set threshold, a decision to adopt is not yet possible. Optional additional global weights that can be applied to offer the possibility to account for specific circumstances in all companies, e.g. by simulating only very tech-averse or high-tech companies. For all external and internal factors explained in tables 1 and 2, weights will be introduced as a variable (inertia and desire weights). This variable can be used to adjust the corresponding factor for later analysis.

$$\text{inertia weights} = inert_{emp}, inert_{man}, inert_{in_{know}}, inert_{in_{res}}, inert_{pre_{cus}}, inert_{pre_{mar}} \in \mathbb{R}_0 \quad (1)$$

$$\text{inertia (in relation to the availability)} = \quad (2)$$

$$inert_{av} = inert_{av-1} - (av + inert_{emp} * emp + inert_{man} * man + inert_{in_{know}} * in_{know} + inert_{in_{res}} * in_{res} + inert_{pre_{cus}} * pre_{cus} + inert_{pre_{mar}} * pre_{mar})$$

To decide whether a company is inclined to adopt the spread of quantum computer-safe cryptography measures, a variable that reflects that internal state of mind is needed. This “desire to adopt” will be used as the initial baseline for a company’s willingness to adopt (Eq. 4). External and internal influences that interact with the agent during a simulation can influence this value either to increase or decrease the future probability of adoption. This is done by tracking the developments in the company using costs (Eq. 3). Higher costs will require more internal resources or funds. The closer the available funds are to the perceived costs the higher the probability of an organisation considering the adaption from a financial point of view. The perceived costs will be offset with the calculated funds and then normalized using a sigmoid function to fit the result to a usable probability for use in Eq. 6.

$$\text{costs for adoption} = cost = [0, 1] \quad (3)$$

$$\text{probability for the influence of financial related values} = \quad (4)$$

$$prob_{cost} = {}^{1}\!/_{(1 + e^{-5(funds - cost + 0.5)})}$$

Each agent’s decision to adopt will be based on their desire for adoption influenced by these factors: calculated cost value, market and customer pressure, legal influences and the compound value from the social link values represented by communication. The factors multiplied with their corresponding weights added together are normalized with a sigmoid function. A sigmoid function in the form of a curve instead of a linear approach is used to try to emulate human behaviour in their willingness to accept new information early on but getting harder to fully convince. The normal sigmoid function will map the value 0 (i.e. all factors being 0) to a probability of 50%. To reach a probability of close to 0% when all influencing factors are either 0 or negative, a necessary shift on the x-axis to the right was calculated to be 2.7. This value offers an approximation for 0 with 0.0623 and all factors being 1 with 0.9864. The miniscule chance to adopt the new technology even when the factors are unfavorable is intended to account for the unpredictability in human behaviour. Similarly, the upper boundary only approximates the 100% to account for other influences outside of the model and possible interferences.

This desire will be used after the inertia threshold is reached to decide for each instance of the simulation if the agent adopts the new technology or not. The desire will change depending on the initial setting but will increase with the growing market pressure and internal resources (Eq. 5 and 6).

$$\text{desire weights (adjustments to the influence of the factors on the desire)} = d_{{prob}_{cost}}, d_{{pre}_{cus}}, d_{{pre}_{mar}}, d_{com}, d_{leg}, d_{man}, d_{emp} \in \mathbb{R}_0 \tag{5}$$

$$\text{desire to adopt (probability to adopt new tech)} = 1 \Big/ \left(1 + e^{-\begin{pmatrix} d_{{prob}_{cost}} * prob_{cost} + d_{{pre}_{cus}} * pre_{cus} + d_{{pre}_{mar}} * pre_{mar} + \\ d_{com} * com + d_{{gov}_{leg}} * gov_{leg} + d_{man} * man + d_{emp} * emp - 2.7 \end{pmatrix}}\right) \tag{6}$$

4. Future simulation scenarios

To create different simulation scenarios which can be explored during future research, the desire weights can be adjusted individually and step by step to analyse if and how these factors impact the whole simulation. The social link will be used as a representation of the influence of communication and other social aspects (like a strong dependence) between agents (e.g. with subsidiary companies, the government, or providers of standardized solutions). Because of this dependence, the influence of strongly linked agents on the probability of adoption on each other is higher than with other agents. While the following main scenarios are planned, additional scenarios can be created later.

4.1 Random runs (acting as a baseline)

Multiple random distributed values for the internal and external factors will be generated and used for multiple thousand simulation runs. A detailed statistical analysis can then be used to identify valuable information about the behaviour of the agents (e.g. to recognize emergent phenomena) and the overall performance of the simulations over a widespread and diverse distribution.

The values of runs that showed a relevant distribution of quantum computer-safe encryption measures (either because the distribution was very successful or not at all successful) will be kept as a baseline for a more detailed analysis during further runs. Criteria for the performance of a simulation like the time needed for a spread between all agents or the thoroughness of the spread can be used to decide which runs could be investigated further.

4.2 Improved runs

Based on knowledge gained from the previous random runs, weights and values for internal and external influences will be set to successful or interesting value ranges identified in prior random runs. These could include the minimum, maximum, average, median and interesting value ranges. These value ranges can be refined through multiple iterations. To find out which values show what kind of influence, the values can be copied from existing random runs that are worth consideration for a more detailed analysis. A single value will be changed for an improved run, to discern the influence of it on the simulation result. This can be done multiple times with different values. This approach allows for a more detailed review of relevant data sets that were not covered by the random runs.

4.3 Governmental influence

To demonstrate the governmental influence, the government is represented as an agent in this scenario, as opposed to just being an external influence. It is modelled as one agent having a social link with all other agents for this simulation. The link can be weighted to model a stronger or weaker influence on the governmental side and on the side of the companies.

Multiple runs can be used to compare individual value settings, in this case in the category of governmental influence. This way, the strength of influence on diffusion and the values which influence diffusion most during the simulation can be identified. For the governmental influence, two areas of influence will be considered: financial and legal. While the financial influence can impact the costs companies face during adoption, the legal influence can impact their desire to adopt.

Financial influence. The government as one central agent incentivizes other agents with subsidies (supporting companies with providing the full cost, half the costs or a quarter of the costs for adoption).

Legal influence. The government as one central agent forces other agents to adapt to legal boundaries and punishes non-compliance.

By exploring the scenario, comparisons can be made on which force of influence is most effective at supporting the spread of quantum computer-safe encryption measures in the market.

4.4 Top-down influence by companies

One or few big companies with a positive social link to multiple agents (e.g. providers of standardized software solutions, IT consulting companies or companies with a lot of partners or contractors) can spread information between them and influence their adoption decisions. The social link can vary with different values. Differences in these social link values can be used to analyse the impact of this influence. If the values for internal factors in such a big company are close to 1 and the weights for these aspects are also increased, inertia is reduced faster for this company. Through this scenario, it’s possible to explore whether a top-down diffusion of technology adoption is successful. If so, standardized solutions provided by a few big companies could be used to increase market coverage without smaller companies having to create their own solutions.

4.5 Bottom-up influence by companies

Multiple adoption-interested companies try to influence more complex organizations to facilitate a wider spread of adoption. This way, it can be observed how market pressure influences diffusion. Agents with less ties to other companies (usually represented by a social link) could be characterized as smaller companies in this regard to represent them having less influence on others than a big company. These small, adoption-interested companies can be characterized with high values in internal factors to reflect their willingness to adopt and increase the clearing of inertia compared to other agents.

5. Future research

The proposed central elements for an agent-based simulation model can be implemented into a fully functional simulation model during later research. Such a model could be used to explore how different conditions in the market could influence the spread of quantum computer-safe encryption measures in the market positively or negatively. Based on these simulations, recommendations could be inferred that could put all market participants in the best position to be able to adopt the measures that are needed to protect themselves from the possible dangers of quantum computers adequately.

Of course, the proposed model is subject to certain limitations. As no actual market data could be used and certain abstractions had to be done, the model is unable to account for all possible influences inside or outside the market (e.g. foreign influences). Because of the explorative nature of the simulation, the results are subject to uncertainties. This also applies to assumptions that had to be made like the details of the used sigmoid function.

The implementation of this model will be addressed by the authors in the future. After implementation, simulation scenarios will be run according to the above order. The results of these simulations will be evaluated and used to infer recommendations for relevant market participants to support the adoption of quantum computer-safe encryption measures throughout the market.

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