Artificial Intelligence and its Applications

Introduction

YourMoney is a start-up building society with opportunities to increase efficiencies and customer satisfaction through Artificial Intelligence (AI).

Three AI use cases are proposed with benefits, risks and data requirements discussed for each.

YourMoney Building Society

YourMoney is a start-up building society offering savings and current accounts, loans, mortgages and credit cards.

Key Performance Indicator (KPI) groups in financial and risk categories are shown in figure 2, derived from KPMG (2016).

Category	KPI Group
Financial	Profitability ratios
	Mortgage lending, including all loans secured on property or land.
	Reserves and capital
Risk	Loan to Value indexing
	Loans past due or impaired

Figure 1. KPI Summary derived from KPGN (2016)

The challenge is balancing risk and income; attracting new business whilst not taking unacceptable risk. Financial services is heavily regulated so operations need to be compliant and auditable.

AI Opportunities

AI adoption is growing in financial services and is becoming a key competitive differentiator, as noted by Linklaters (2018):

> "The winners and losers in the new digital banking landscape will be defined by those that can best access, process and analyse data, the speed with which they can react to such analysis, and their ability to predict and control the increasingly autonomous activities of their IT systems."

They note challenges including ensuring algorithms don't make discriminatory decisions that might be unethical or unlawful, with Ostmann & Dorobantu (2021) highlighting similar benefits and risks.

Van Niekerk & Subramanian (2022) also note that there are many opportunities to use AI in financial services, but each comes with different benefits and risks so it is important to select the right use case based on value and feasibility.

Berns (2020) found that most executives from financial institutions across Germany, Austria and Switzerland are looking for AI to deliver conventional benefits such as increased efficiency (79%) and cost savings (73%) – figure 2.

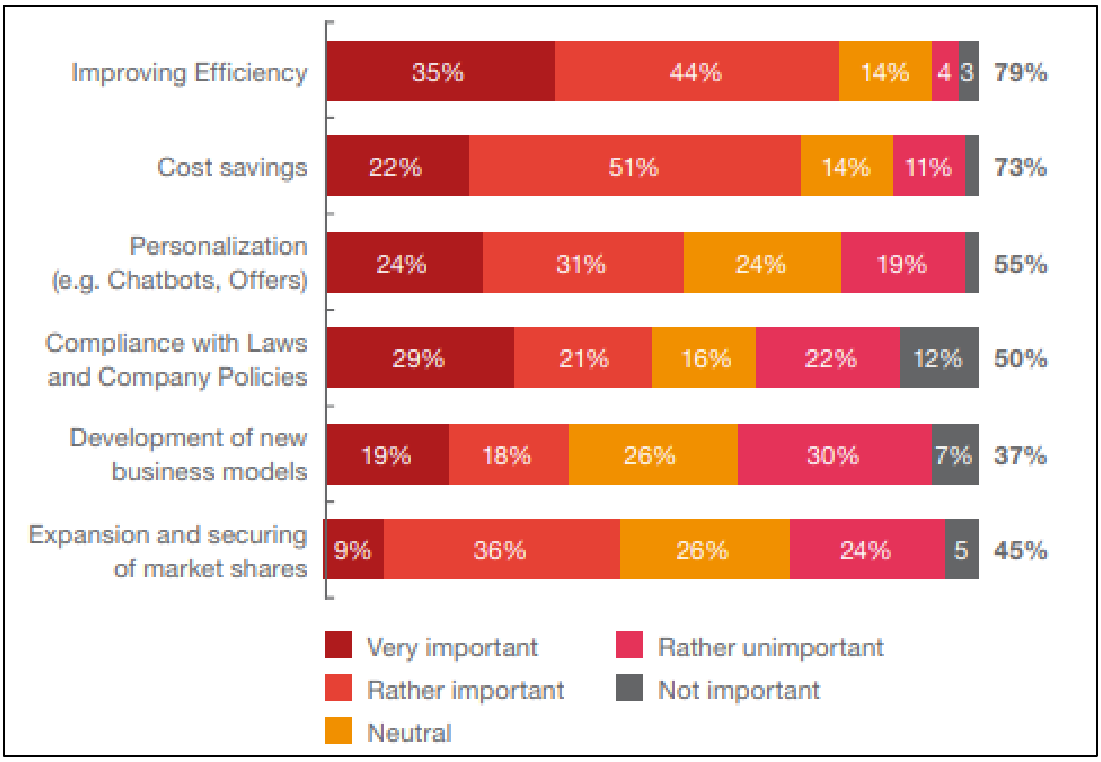

Figure 2. Important fields of application for AI (Berns, 2022).

With those benefits and cautions in mind, three AI use cases are proposed. All require data to be provided by domain experts from YourMoney so the CRISP-DM process (Wirth & Hipp, 2000) is recommended to ensure a structured approach for data capture, preparation, modelling and deployment.

Virtual Agent

Banks and building societies face increasing volumes of customer calls and emails due to growth and expanding product lines leading to increased costs, so many are turning to virtual agents (Chan et al, 2019).

A virtual agent would reduce costs by handling routine contacts without human intervention, and increase customer satisfaction by dealing with simple enquiries 24/7 because YourMoney answers calls and emails during UK office hours.

The proposal is to build a virtual agent using Natural Language Processing (NLP) on a platform such as IBM Watson, Google's Dialogflow or Microsoft Bot Framework, as suggested by Kvale (2020) and Pérez-Soler et al (2021). This would enable fast start-up because core language training data is already provided, even including a basic financial services agent (Google, N.D.a) so domain experts from YourMoney would initially only need to provide training data to cover their products. Training would be iterative whereby training data is added and the virtual agent is tested, iterating with more data until it is able to answer most questions.

Dialogflow uses two algorithms simultaneously; rule-based grammar matching and Machine Learning (ML) matching (Google, N.D.b). This would allow quick deployment of an initial solution using rule-based grammar matching to answer simple questions such as "what is my balance?" and "when does my mortgage fixed rate end?". The next iteration could integrate into additional systems to take actions such as stopping a credit card in response to "my credit card has been stolen". Over time, as the ML matching has more training data added, the conversational language would become more natural and easy to use.

If YourMoney does not want a cloud solution, a simple rules-based virtual agent could be deployed using Artificial Intelligence Markup Language (AIML) as explained by Lalwani et al (2021).

The virtual agent would have access to personal information so it would be vital to include data encryption and authentication. It could answer general enquiries whilst unauthenticated.

Loan Application Assistant

The application process for mortgages and unsecured loans at YourMoney is time-consuming. A loan application assistant could take the affordability data for a customer and instantly determine if they qualify for a mortgage or unsecure loan.

Financial Conduct Authority (2022) states that records must be kept of the reason for every mortgage decision, so transparency will be important in the solution. For this reason, Decision Tree (DT) is proposed because DT results are understandable (Russell & Norvig, 2021). The DT would log the decision along with the reasons for complete transparency.

Loan applications also need to validate documents such as bank statements, utility bills and passports. To fully automate the process a document reader could also be included using a Convolutional Neural Network (CNN) (Simard et al, 2003), although there are “off the shelf” document readers so knowledge of the precise algorithm is not necessarily required. The document reader would input data into the DT so the DT would be making the “understandable” decision with the CNN providing auditable inputs.

Initially, the DT would be used with a human agent checking the documents and inputting the required data, with further benefits in a subsequent iteration by adding a document reader.

Benefits include reduced costs due to automation, reduced average time to approve loans and simplified compliance auditing because every decision is stored with reasons from the DT.

The DT would be trained on historic loan applications data and then tested on the remainder using the holdout method (Raschka, 2018). The ratio of training and test data would depend on the amount of data available.

A risk with supervised learning such as DT is the model becomes biased, making decisions using inappropriate criteria (Navarro et al, 2021). To combat bias, domain experts from YourMoney should ensure data that should not be used in the decision is excluded from the algorithm. For example, name, gender and occupation would be necessary to capture, but it would be inappropriate for them to be used in the DT because it could, for example, result in an inadvertently sexist model. Overfitting should also be eliminated with pruning (Russell & Norvig, 2021). With such safeguards in place, the model should be objective, and potentially less prone to bias than human agents.

Data collected would need to be stored securely and in compliance with General Data Protection Regulation (GDPR) (Information Commissioner’s Office, N.D.).

Credit Card Fraud Detection

There is an opportunity to use AI to assess credit card transactions for indicators of fraudulent activity. UK credit card losses from fraud fell from £620.6m in 2019 to £574.2m in 2020, partly as a result of improved protection such as 3D Secure (UK Finance, 2021). There is, however, still a big opportunity to reduce YourMoney's losses and increase customer satisfaction by preventing fraudulent transactions.

The AI would monitor every credit card transaction looking for clues that it does not fit a normal pattern and is potentially fraudulent so it would need to be highly performant. Algorithms such as Support Vector Machine (SVM) are generally better performing than DT (Suhaimi & Abas, 2020; Danso et al, 2014), so would seem an ideal choice. Unfortunately SVM is a "black-box" because unlike DT the reasons for decisions are not obvious. This seems to make it unsuitable for financial services where transparency and explainability are important. However, Gill (2021) notes that AI needs to be explainable "when consequences are radical".

The proposed solution would stop the transaction and put a temporary stop on the card upon detecting a potentially fraudulent transaction, whilst contacting the customer by text to confirm if the transaction was genuine. If confirmation is received the card will be unlocked. This is considered to not be a radical consequence and therefore any algorithm can be used. This is supported by Gyamfi & Abdulai (2021) who recommend SVM for this use case, although they are based in Ghana so subject to different legislation.

WEKA would be used to model historic credit card transaction data using multiple algorithms such as SVM with different kernels plus Artificial Neural Network (ANN) and DT. Stratified 10-fold cross-validation would be used because the data set is highly imbalanced with a small percentage of fraudulent transactions so stratification would ensure the models are trained and tested with both positive and negative class values whilst k-fold maximises the use of the data, using it all for training and testing (Raschka, 2018). Precision, accuracy, sensitivity and specificity would be calculated and discussed with the management team to select the best performing model based upon their requirements, for example minimising false positives (keeping transactions flowing to maintain customer satisfaction) or maximising precision (stopping the highest volume of fraudulent transactions to minimise financial losses).

The transactional data is already anonymous so there are no anticipated data confidentiality risks. The main risks are operational; if the model is over-zealous at stopping transactions. As a first step the model should be deployed passively, monitoring and flagging transactions but without the ability to directly intervene. This would provide safe real-world feedback to YourMoney before full deployment.

Additional Opportunities

There are opportunities to extend the proposed use cases for additional benefits. For example, analysing current and savings account data could provide insights that signal that a customer might be ready to buy a home so they could be proactively marketed with YourMoney mortgage products. Data could be pre-populated into the loan application assistant to give them a pre-approved conditional offer at a certain loan to value level.

Conclusion

Three AI opportunities for YourMoney have been examined; virtual agent using NLP, loan application assistant using DT and CNN, and credit card fraud detection using a best-fit algorithm, likely to be SVM. Benefits, risks and data requirements have been discussed and the recommendation is to deploy all three, starting with a basic capability for each that would be expanded over time.

Safeguards to cover data privacy and ethical AI need to be considered in each solution.

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