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TESI DI LAUREA

"ARTIFICIAL INTELLIGENCE APPLICATIONS IN MARKETING: THE CHATBOT OF THE DEPARTMENT OF ECONOMICS AND MANAGEMENT MARCO FANNO"

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Firma (signature) Giovanni Sambugaro ....

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Ringrazio la mia famiglia, i miei parenti e i miei amici per avermi accompagnato e sostenuto lungo il mio percorso di studi.

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Abstract

Artificial intelligence (AI) offers numerous applications in marketing, but at the same time, there are several limitations to consider in its adoption. After the first part about a general analysis of the applications and negative aspects of AI and chatbots, the thesis focuses on the case of the implementation of a chatbot by the Department of Economics and Management "Marco Fanno" of the University of Padua.

The research question turns towards understanding whether the chatbot implemented by the Department was effective in easing and supporting the work of the administrative office and answering students questions. For this purpose, the paper analyses if the number of emails is decreased after the chatbot introduction.

In addition, a questionnaire was carried out to evaluate the experience that the students of the Department have had with the university chatbot. The survey also asked students what services they would like the chatbot to add to their current ones.

Moreover, an economic analysis on benefits and costs was conducted to estimate whether the chatbot will generate a positive outcome. This study allows evaluating the impact a chatbot could have in the education field. In particular, it can provide insight to universities on whether a chatbot could enhance the engagement with students, offload staff from repetitive tasks and generate net economic benefits in the long period.

The questionnaire itself was conducted through a web survey on Google Forms and a chatbot survey. In this way, it could also be verified which of the two methods is the most effective to conduct a survey. Some evidence finds how chatbot surveys can lead to less satisfactory answers by respondents. Comparing the two survey results, I can verify these past findings with a different sample of participants, the students of Economics.

The results did not show clear evidence of whether the chatbot allowed reducing the number of emails. But an investigation over a longer period is suggested. Then, findings highlighted a good appreciation of students for the chatbot and suggested the introduction of push notifications that remember university deadlines such as taxes. The estimation of the benefits-cost analysis forecasted a net positive outcome over three years with an ROI of 29%. Also, the chatbot survey partially confirmed the encouraging finding in reducing satisficing by respondents.

Introduction

Background

Marketing is evolving continuously. It is possible to count five marketing phases from the 1950s with Marketing 1.0 to nowadays with Marketing 5.0 (Passarella; 2021). In the beginning, the objective of marketing was to sell large quantities of homogeneous products (Marketing 1.0). Then, the attention shifted to offering a personalized offer to customers and building their loyalty (Marketing 2.0). The targeting became crucial. Subsequently, consumers searched for brands with shared values (Marketing 3.0). At this point, they sought the spiritual dimension of the offer proposition combined with the emotional and functional dimensions of the previous phases. The following step was the integration of technology in the marketing strategy (Marketing 4.0).

Nowadays, marketing is the *"*... the application of technologies that mimic the human to create, communicate, offer and increase value along the Consumer Journey." (Kotler, 2021). We understand that for companies, it becomes fundamental to connect the human part to the technological one to effectively reach the consumer through the different stages of the customer journey. The ongoing developments of artificial intelligence (AI) are the driving forces of these changes. Today, the new marketing technologies are expressed in different fields: data-driven marketing, predictive marketing, contextual marketing, augmented marketing, agile marketing.

AI allows collecting numerous data from our connected devices and storing them in a database where the information is associated with a person. Machine and deep learning AI allows discovering correlation and insights from data to exploit for the marketing strategies of companies. Then, AI allows predicting the market evolving and our future preferences. Also, it can scan people faces to understand their emotional state and make offers accordingly. Furthermore, AI can collaborate with people to enhance their experience and monitor the analytics of people to give contextual adjustments to the company processes.

A particular AI field of development is related to the conversational area. In this domain, chatbots are a technology in growing expansion. Indeed, the AI advent allows chatbots not only to communicate with users according to a predefined set of rules but also to adapt their style of interaction to the contextual situation. By 2024, Insider Intelligence (2021) predicts that

consumer retail spending via chatbots worldwide will reach $142 billion—up from just $2.8 billion in 2019.
Chatbots are congenial with the current marketing needs as they can create a personalized interaction with customers on a large scale.

Beyond traditional businesses, a sector that is starting to consider the adoption of chatbots is education. Even in this field, chatbots can offer many benefits: they can assist students in the enrolment appliance, answer more common questions, thus lowering the number of emails received by the secretariat, inform on the study plans provided, encourage students to join extracurricular activities.
There were several cases of universities that experienced success with chatbot adoption. For instance, Winston-Salem State University (WSSU) in 2017 noted that email and phone communication were not engaging enough to help new students prepare for the college experience and so decided to adopt a chatbot (Mainstay, 2020). One of the principal purposes of the chatbot was to assist students in completing enrolment steps about immunization compliance and bill payment. The results were significant: the university registered a 2% increase in enrolment from the chatbot adoption.

In this thesis, I examined the impact a chatbot could have on a university by considering the students' satisfaction with the technology, whether it allows lowering the number of emails received and its cost and potential benefits generated.

In addition, I investigated the chatbot application in surveys.
Chatbot surveys can offer a valid alternative to classical web surveys. Kim et al. (2019) report as web surveys often are subject to satisficing behaviours. It happens because respondents have to put substantial cognitive effort to optimally answer a survey question. Therefore, some simply provide a satisfactory answer to reduce the workload (Krosnick, 1990). Satisficing may lead respondents to adopt some strategy to save mind work as give homogeneous replies to many questions in succession.
In their study, Kim et al. (2019) show as a chatbot survey can reduce this negative behaviour.

Problem statement and relevance of the study

On 16 April 2021, the Department of Economics and Management "Marco Fanno" of the University of Padua adopted a chatbot. Its purpose was to provide a 24/24h assistant to current and future students by allowing them to have an answer to more common questions. Therefore, the secretariat and the tutoring service should receive fewer contact requests (emails, calls, meeting in presence) compared to the situation precedent the chatbot introduction.
This study aims to respond to two main research questions.

The first and the broader one is: **RQ1: Was the adoption of the chatbot of Economics positive in terms of reduction of the email received (RQ1.1), user satisfaction and potentialities of its features (RQ1.2), and economic impact (RQ1.3)?**

The research is relevant because it allows understanding the effectiveness of this new tool in a sector, education, for which it represents a novelty.

Student satisfaction was measured (RQ1.2) through a questionnaire distributed in two ways: a web survey on Google Forms and a chatbot survey. The two methods allow comparing which one is better in surveying. Hence, the second research question is **RQ 2) Could a chatbot survey be more effective than the classical web survey distributed with Google Forms?**

I proposed the experiment of Kim et al. (2019) with a different sample of participants -the student of the Department of Economics of Padua- to compare the results and show eventual differences.

Research methods

To respond to RQ1.1, I used the reports of the tutor about the contact requests received. For RQ1.2, I surveyed the students of the Department of Economics. For RQ1.3, I considered the expenses of the Department of the chatbot, and I estimated the potential savings and revenue by basing on other case studies and some assumptions.
For RQ2, I compared the results of the web and chatbot survey to analyse which of the two respondents have appreciated more; then I calculated the index of response differentiation (Pd) to measure satisficing.

Dissertation Outline

Chapter 1 presents a general overview of the contribution of AI to marketing and lists its benefits and pitfalls. Chapter 2 describes chatbots and their application in marketing.
In Chapter 3, the research on the chatbot of Economics and chatbot surveys is discussed.

Chapter 1

Contribution of artificial intelligence to marketing and its current limits

1.1 What is artificial intelligence?

There is a lot of confusion surrounding the term Artificial Intelligence, so it is useful to describe what could be included in this category. For this reason, two main divisions could be selected: the "weak" Artificial Intelligence and the "strong" Artificial Intelligence.
For the first terminology, an artificial intelligence problem is to make a machine behave in a way that would be called intelligent if a human was so behaving (McCarthy, Minsky, Rochester, & Shannon, 1955). It is an intelligence that can learn to perform only a specific and well-defined task, such as playing chess, recognizing human faces, predicting the likelihood an online visitor will click on an advertisement banner (De Bruyn et al., 2020). Instead, "strong AI" (Kurzweil, 2005) refers to a machine that can "learn how to learn". Therefore, the machine can adjust its algorithm over time to adapt to changing demands and external conditions. "Strong AI" thinks like humans, draws on general knowledge, imitates common sense, threatens to become self-aware, and takes over the world (Jim Sterne 2017, p. 10). It is associated with the concept of machine learning that will be treated in the next paragraph.

1.1.1 Machine learning

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E (Mitchell, 1997). Sterne (2017) gives a practical example of how machine learning works (fig.1). The example provides a clue on how machine learning understands from past wrong predictions and consequently adjusts its reasoning for new future problems.
In this way, the machine learns from experience and write its code without the intervention of the human. Some problems could arise once the problems assigned to the machine become complex and the machine start to run very articulated algorithms of difficult interpretation.

In this case, it is difficult for data analysts to understand how to draw some conclusions from the machine elaborations and this is one of the pitfalls of machine learning that is covered in section 1.3.2.

Nowadays, the effectiveness of machine learning is provided by the possibility to collect an enormous amount of data from consumers, thanks to Internet technologies.

The dataset can be both long and wide (Yeomans, 2015). Long because of the vast number of customers collectable. Wide because each customer can have a large number of variables and traits identifying him.

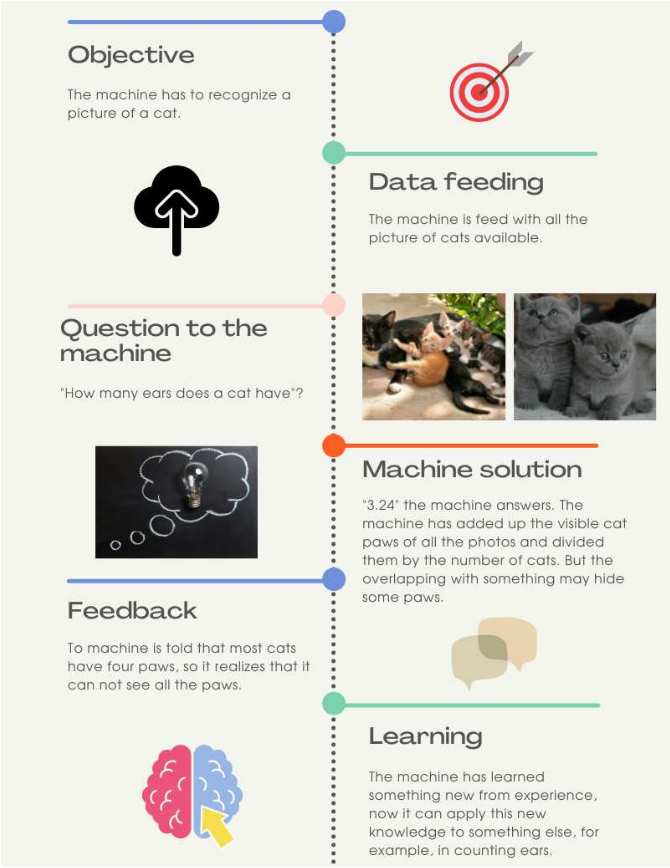

Figure 1: example of how a machine learns from experience.

1.1.2 Deep Learning

With the advent of deep learning, a lot of very complicated AI processes are dramatically improved, such as speech recognition, visual object recognition, object detections, drugs discovery and many others. Deep learning tries to solve tasks hard to describe formally, requiring a lot of experience and knowledge. It tries to achieve them by learning complicated concepts that are built on simpler ones. The term “deep” is adopted because if a graph is drawn showing how these concepts are built upon each other, the graph is deep, with many layers (Goodfellow, Bengio, Courville, 2016).

Deep learning is a class of machine learning based on two concepts: artificial neural network and representation learning.

Artificial neural networks are computational models inspired by the nervous system of living beings. They can acquire and maintain knowledge (information-based) and can be defined as a set of processing units, represented by artificial neurons, interlinked by a lot of interconnections (artificial synapses), implemented by vectors and matrices of synaptic weights (Da Silva et al., 2017). Fig.2 represents an artificial neuron, in which the output depends on a set of input weighted for their importance. The weights to assign have to be learned with experience and a neuron compute a non-linear function over the inputs.

In fig. 3 a simple example of an AI function that has to determine whether the animal is a cat or a dog by basing on the weight and length variables.

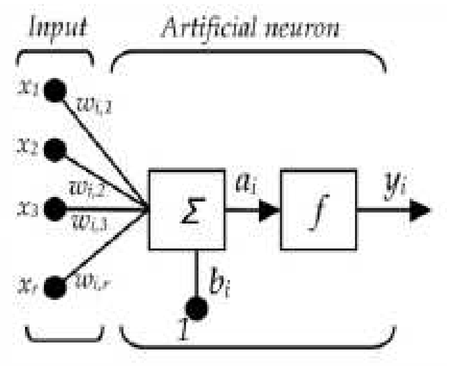

Figure 2: artificial neuron, source: Luca Pasa (2020).

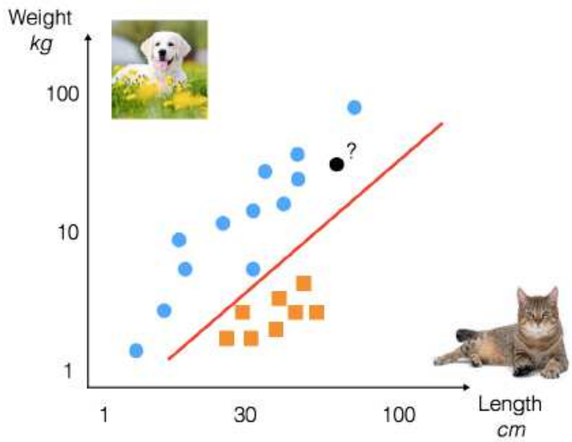

Figure 3: a simple example of an AI function that has to determine whether the animal is a cat or a dog by basing on the weight and length variables. Source: Pasa (2020).

Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification (LeCun, Bengio, & Hinton, 2015).

Therefore, deep learning can be defined as a representation-learning method with multiple levels of representation, obtained by composing simple but non-linear modules. Each module transforms the representation at one level into a representation at a higher, slightly more abstract level of complexity (LeCun, Bengio, & Hinton, 2015).

In practice, deep learning allows building complex concepts out of simpler concepts. In figure 4, it is visible how deep learning works in image recognition: the machine breaks up the image in its pixels and from these, it gradually starts to compose more complex layers, obtaining the edges, the corners and contours, the object parts and finally the object identity.

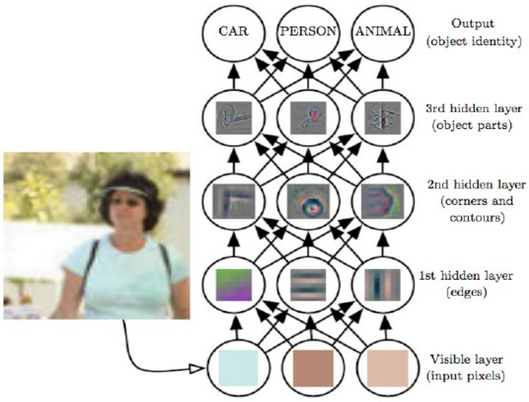

Figure 4: example of an image detection process through deep learning. Source: Sperduti (2020).

1.1.3 The learning paradigms by which the AI learns

Artificial intelligence algorithms can process and learn from data in different ways, and knowing the different methods by which they can be executed, allows one to choose the most appropriate approach to apply in the required AI application.
Three main learning paradigms could be identified: supervised learning, unsupervised learning and reinforcement learning.

Supervised learning

In a supervised learning paradigm, a neural network learns from a set of examples (training data) where both inputs (predictors) and outputs (target variables) are known to the AI analyst (De Bruyn, 2020). In this case, the algorithm grounds on a labelled dataset, a list of appropriate actions the system has to take in a particular situation. The objective is to extrapolate or generalize its responses so that it acts correctly in situations not present in the training set (Sutton & Barto, 2018).
For instance, it can be considered the case of a firm that wants to know if a customer is satisfied with the company product by analysing the comments on socials or the web reviews. First, a human operator has to label these comments in angry/not angry categories, then the algorithm can use these inputs to calibrate the predictive model.
Sterne (2017) compare supervised learning to a father teaching his son to recognize a cat. The son has an example and a label and can now on his own recognize a cat. This is a simple example but it helps to understand the initial role a company has in providing a list of labelled instances

from which the machine can learn. In this way, the machine will apply the knowledge acquired in future problems to solve.
Supervised learning is appropriate for two types of problems (Delua, 2021): classification and regression. The first is useful for assigning test data into specific categories, for instance, to classify spam from the rest of emails. The latter is useful to find the relation between the dependents and the independent variables from a training database, and use the correlation founded to predict future outputs from a set of new inputs.
For instance, if a firm wants to predict its sales revenue from a set of variables – as could be the number of customers, the amount spent in advertising, the number of salespeople - it should: first, analyse the historical correlation between these variables and the value it wants to predict; second, from the gotten relation, built the model to adopt for future predictions.

Unsupervised learning

Unsupervised learning helps find patterns in data without pre-existing labels (De Bruyn, 2020). These algorithms discover hidden patterns in data without the need for human intervention (for this reason they are "unsupervised") (Delua, 2021). They are particularly useful to get insight from a large set of data where there is not known in advance what to search and what is the relationship between the variables. They are used for three types of tasks: clustering, association, dimensionality reduction (Delua, 2021). The first is a technique to group unlabelled data for their similarities or differences. An example of the clustering method is the k-means, which assign similar data points into groups where the k value represents the size of the grouping. Association is a technique adapts to find a relationship between variables in a given dataset and it can be used for recommendation systems. Dimensionality reduction is a technique to discard non-significative data from a very large database.
Sterne (2017) compares unsupervised learning to an infant who alone tries to understand what are the objects around him by doing hypotheses and tests. Although until now, this method is less adopted than the more traditional supervised learning, it is predicted to assume more importance in the long term (Nature, 2015). Furthermore, it is the learning approach that most humans and animals apply in their life as they discover many new things without an outside supervisor teaching them. Hence it is plausible a larger adoption of unsupervised learning in the future.

Reinforcement learning

Reinforcement learning (Sutton & Barto, 2018) is an area of machine learning where an agent learns to take actions in an environment to maximize rewards and minimize penalties over time. Reinforcement learning maximizes function f(S, A)→ R, where R is the reward, S is the state of the environment and A is the set of actions an agent could take. It could appear similar to unsupervised learning since these learning paradigms do not rely on a labelled example of correct behaviour, but while the first search for hidden relationships among data, reinforcement learning search to maximize a reward function. Reinforcement learning has to balance exploration and exploitation dimensions. It is a trade-off since exploration is necessary to discover better actions to take in the future, while exploitation is necessary to get the maximum from what it has already experienced (Sutton & Barto, 2018).
Sterne (2017) compares reinforcement learning to a father that corrects his son when he makes a mistake and praises him when he gets it right. Companies apply reinforcement learning by designing the function to be maximized and the constraints that the algorithm has to respect to bring the algorithm to an optimal result.
Organizations can successful apply reinforcement learning for real-time optimization tasks such as website designing, online advertising and pricing problems (De Bruyn, 2020).
Reinforcement learning compared to other methods has the advantage of being immediately useful, since the algorithm has a clear maximization function to follow, which coincides with the goal that a company adopting this paradigm wants to pursue. Instead, the other learning paradigms find some sort of results autonomously and then the company has to find some sort of utility from them. For example, an unsupervised learning algorithm could clusters classes of similar customers, but it will be a task of the company to understand if this classification is significant and useful for the company purpose.

However, especially for reinforcement learning, it is very important to take a holistic approach to set the function to be maximized, because machines lack common sense. Things that are certain for man are not certain for machines. For this reason, it is essential to establish a complete set of constraints that the machine has to respect to avoid un desiderated actions. This part is discussed more deeply in par. 1.3.2.

1.2 The contribution of artificial intelligence to marketing:

1.2.1 Artificial Intelligence statistics

Artificial intelligence is having an even more great impact on marketing. McKinsey Global Institute predicts that AI and machine learning are on track to create between €1.18 trillion to €2.20 trillion in value by solving marketing and sales problems. The marketers' use of AI increased from 29% in 2018 to 84% in 2020, according to Salesforce Research's State of Marketing Study (2020). Coherently, there is been a 76% increase in sales professionals adopting AI-based apps and tools, with high performing sales organizations being 2.8 times more likely to use AI than less performing ones (fig.5).

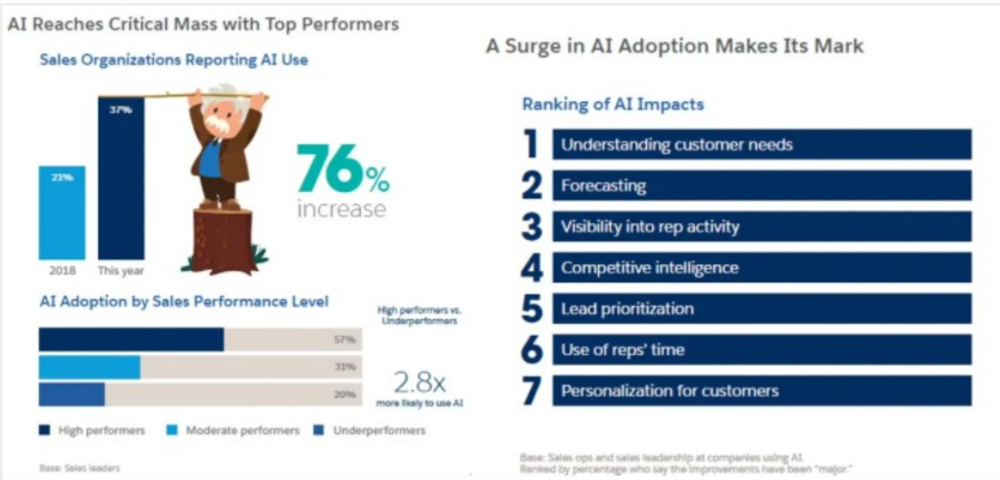

Figure 5: data about the state of adoption of AI. Source: Salesforce (2020).

Marketing and sales are the functions recording the larger revenue increases thanks to AI adoption (fig.6), with about 40% of the firms recording an increase higher than 6% (McKinsey, 2020). However, marketing and sales lag behind other departments on cost savings (McKinsey, 2020).

According to the 2019 CMO survey on a sample of 323 companies with sales revenues ranging from less than $ 25M to more than $ 100B, figure 6 shows the marketing activities having the highest adoption of artificial intelligence. Considering companies with revenues of 100-499M, there is a considerable percentage of AI tools adoption for predictive analytics (77.8%) and conversational agent (88.9%).

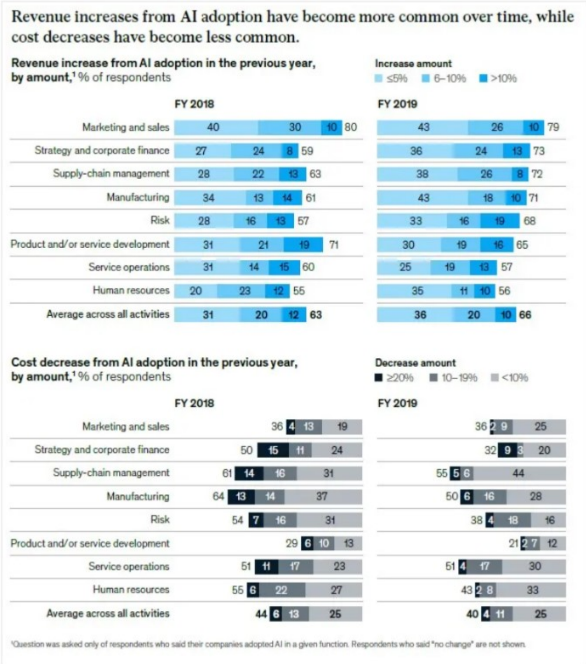

Figure 6: impact of AI adoption on revenues and costs. Source: McKinsey & Company (2020).

How is your company using AI in its marketing activities? (check all that apply) - % Selected

Activity	Overall	B2B Product	B2B Services	B2C Product	B2C Services
Content personalization	56.5%	57.1%	62.2%	61.9%	40.9%
Predictive analytics for customer insights	56.5%	54.3%	48.6%	61.9%	68.2%
Targeting decisions	49.6%	37.1%	40.5%	61.9%	72.7%
Customer segmentation	40.9%	34.3%	32.4%	61.9%	45.5%
Programmatic advertising and media buying	38.3%	31.4%	29.7%	42.9%	59.1%
Improving marketing ROI by optimizing marketing content and timing	33.9%	31.4%	35.1%	28.6%	40.9%
Conversational AI for customer service	25.2%	22.9%	24.3%	19.0%	36.4%
Next best offer	14.8%	5.7%	21.6%	9.5%	22.7%
Augmented and virtual reality	10.4%	11.4%	10.8%	9.5%	9.1%
Autonomous objects/systems	2.6%	2.9%	0.0%	4.8%	4.5%
Facial recognition and visual search	1.7%	2.9%	2.7%	0.0%	0.0%
Biometrics, also known as chipping	0.0%	0.0%	0.0%	0.0%	0.0%

Insights

Over half of respondents are utilizing AI technologies for content personalization and generating customer insights using predictive analytics.

B2C Services companies use, on average, more AI in their marketing activities than other sectors. B2C Product Companies lead on use of AI for customer segmentation and autonomous objects while B2B companies lead in the use of augmented and virtual reality.

Figure 7: top uses of AI in marketing, by company revenue. Source: The CMO Survey(2019).

Fig.7 shows the business motivation for using AI among companies that have yet to adopt it and the reasons reserving firms to implement AI (Bain & Company, 2020). Among the reasons, there is uncertainty about the value that AI could bring to the company and the lack of adequate skills within the company to exploit the potential of these tools. Artificial intelligence is perceived as risky since good managers recognize that only a complete integration of AI with the business firm makes the investment in AI valuable. The 2020 McKinsey report on AI state points out the factors that the most performing firms share in the adoption of artificial intelligence. The keys ones regard:

- Strategy: the development of the AI program is originated bottom-up by the business, and the senior management is fully aligned and committed to the project.

- Talent and leadership: the partnership with lead technology companies to upgrade the AI skills of workers and the education of senior management with dedicated courses on AI. Management must know what AI allows to have the possibility to effectively communicate with AI experts. Indeed if management knows the opportunities the AI provides, it can better realize how it can help the business and communicate what the AI team should implement to improve the current operations (Sterne, 2017).

- Technology adoption: after the installation of AI, successful implementation requires the alignment of people in changing their way of working to be fully committed to the new processes. Moreover, the integration of AI experts within the firm could help to smooth the technology transition.

All these data are signalling the importance for companies to quickly adopt AI in their process to be not left behind in the race to integrate these technologies. But as mentioned before, it is fundamental that the technology is tailored to the business problem. Sometimes, the implementation of AI risks being a shiny object to proudly expose, resulting in an expensive and wasteful investment. Instead, the company must first calibrate the AI for the "why" it wants to achieve to fully exploit the outputs provided by it. Having a clear purpose allows setting a set of objectives to reach and having a list of parameters to evaluate the efficacy of the new AI technologies. In this way, the process is accurately monitored, and the firm can understand if the goals have been reached or how much they are far from their achievement. Otherwise, there is the risk that the company makes a blind bet and finds itself groping in search of some fortuitous application.

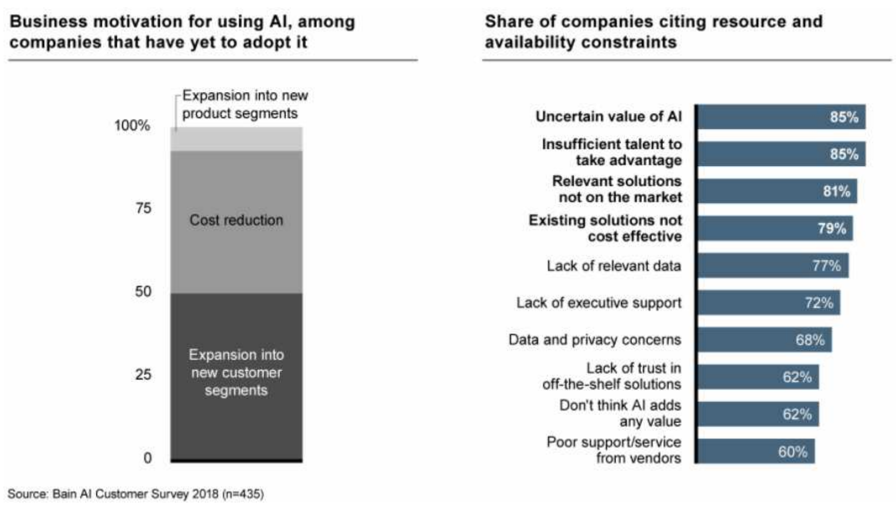

Figure 8: motivations and constraints in adopting AI. Source: Renno & Sinha (2020).

1.2.2 AI strategic frameworks

Different tasks need various levels of complexity. Huang et al. (2019) point out three different levels of intelligence. In order of complexity, they are :

Mechanical: the form of intelligence associated with repetitive tasks. This typology is adapted for tasks requiring high standardisation, in which the machine does not require flexibility but consistency and reliability.

•Thinking intelligence: the form associated with the ability to make decisions. It allows the machine to systematically learn and adapt from data autonomously.

Feeling intelligence: the form able to learn and adapt from contextual data, based on the understanding of feelings and experiences. This intelligence can recognize human emotions and respond in an emotionally appropriate way. The full achievement of this type of intelligence is destined for the future.

In successive research, Huang et al. (2020) assign these three typologies of intelligence to the various phases of the marketing activities, in a way that could leverage the peculiarities of each form. They consider marketing activities consisting of three main segments: marketing research, marketing strategy and marketing action. Each of these marketing activities applies mechanical, thinking and feeling intelligence according to the task need. In fig. 9 and 10 a summary of the appropriate use of the various intelligence forms for each task.

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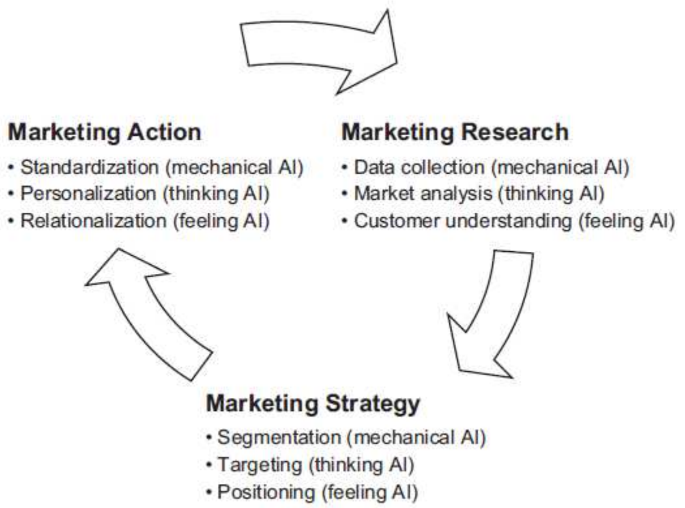


Figure 9: AI and strategic marketing decisions. Source: Huang & Rust (2020).

As the table show (fig.10), each marketing step can exploit the three AI intelligence for some of its tasks.

Mechanical AI

Mechanical AI can be efficiently implemented for data collection through the Internet of Things technologies and web analytics software. Therefore, it is possible to have a broad overview of the characteristics of the consumer, his attitudes, his psychographic data and information regarding the status of the company's products. All these data will be useful later to design a tailor-made product/service offer for the consumer. Moreover, mechanical AI technologies can be used to segment the market, by grouping together customers with similar needs and wants. For example, some parameters of segmentation could be gender, the wiliness to pay, the location. For marketing actions, mechanical AI can be implemented for autonomous payment methods, for service robots with routine tasks, for consumption tracking and order refilling, for automating advertising media planning.

Thinking AI

Thinking AI can be used for the marketing analysis of competitors or to identify new options in a different market. For instance, marketers could use it to predict future fashion trends or future orders by customers. Considering marketing strategy, it can be used for the targeting analysis to select the best segment in which to focus the marketing efforts. In this way, it is possible to optimize the investment return, not considering the customers being not in line with the business offer. For marketing actions, some of the uses of thinking AI could be the personalization of products based on customer preferences, setting the optimal product price, improving the customer shopping experience by using facial recognition software that identifies each client to provide tailored offers.

Feeling AI

Feeling AI can be used for marketing research to analyse emotional data about the level of satisfaction with the firm product. Considering marketing strategy, it can be used for the brand positioning, helping to select the ideal company statement that could breach the customer sentiment. Instead, for marketing actions, feeling AI can be adopted for the following uses: engage chatbots in empathetic conversations, effectively negotiate the price with customers thanks to the emotional intelligence of AI, enhance customer interaction with service robots, track real-time customer response to promotional messages.

AI intelligence Strategic decision	Mechanical AI	Thinking AI	Feeling AI
Marketing research	*Data collection* Automate continuous market and customer data sensing, tracking, collecting, and processing	*Market analysis* Use marketing analytics to identify competitors and competitive advantages	*Customer understanding* Use emotional data and customer analytics to understand existing and potential customer needs and wants
Marketing strategy (STP)	*Segmentation* Use mechanical AI to identify novel customer preference patterns	*Targeting* Use thinking AI to recommend the best target segments	*Positioning* Use feeling AI to develop positioning that resonates with customers
Marketing action (4Ps/4Cs)	*Standardization*	*Personalization*	*Relationalization*
Product/Consumer	Automate the process and output of meeting customer needs and wants	Personalize products based on customer preferences	Understand and meet customer emotional needs and wants
Price/Cost	Automate the process of price setting and payment	Personalize prices based on customer willingness to pay	Negotiate price and justify the cost interactively
Place/Convenience	Automate customer access to product	Personalize frontline interactions	Personalize experience for customer engagement
Promotion/Communication	Automate communication with customers	Customize promotional content for personal communication	Tailor communication based on customer emotional preferences and reactions

Figure 10: how the different types of intelligence are adopted in marketing. Source: Huang & Rust (2020).

Another framework is the one proposed by Davenport et al. (2019), analysing the impact of AI on the different marketing activities, according to the AI intelligence level and the task type considered and wheatear AI is embedded in a robot. In fig.11 is illustrated the framework.

The level of intelligence considered is task automation versus context-awareness. Task automation concerns the grade by which machines accomplishes standardized AI applications. A high-task automated application operates in a well structured and defined context in which it has to perform a specified task. Instead, context-awareness is a form of intelligence that requires machines and algorithms to "learn how to learn" and extend beyond their initial programming by humans (Davenport et al., 2019). In this case, the machine can adapt to the context by considering the variation or the addition of other factors to integrate, according to a holistic and idiosyncratic approach. The output is a tailored answer for every specific situation.

Looking at the framework of Davenport et al. (2019)(fig.11), task type refers to whether the AI application analyses numbers versus non-numeric data (e.g., text, voice, images, or facial expressions).

1) *Controller of numerical data*

Considering fig.11, controller of numerical data is the AI digital form applied for the analysis of numbers. An example of the application of this technology is Kanetix, a company that helps Canadians find an optimal insurance contract. At this scope, the firm has developed an AI application that starting from the analysis of a large amount of numeric data, indicates the customers that are willing to buy but doubtful yet. These are the customers to target advertising efforts, as customers who are very reluctant to buy are difficult to convince, and customers who are already willing to buy will purchase the product even without the promotion.

2) Controller of Data

Controller of data is the AI digital form able to analyse text, voices, faces and images, in addition to numbers. An example of this application is in Stitch Fix, a fashion company that has changed the paradigm of the "shopping-then-shipping" to the "shipping-then-shopping" model, in which the customer receives from home a bundle of clothes without he needs to be engaged in a formal shopping task. The company choose the package of clothes to send according to customer style surveys and likes on social media. Text comments, videos, images are all analysed by the machine learning software getting out the preferences by which to create the sample of clothes. Once the pack arrived, the customer can select the items he desires and give back the other ones that do not satisfy him. It is a new business model that offers the value proposition to try to fulfil the unexpressed desires of customers, to anticipate what people want but of which they are not yet aware.

3) Numerical Data Robot

In a Numerical data robot, the AI is embedded in a robot able to analyse numbers. An example is the robot barista of Café X. This robot can receive the order a customer has added by a touchscreen. Each order is a numerical input that the machine converts in a request to be executed.

4) Data Robot

In a Data robot, the AI is embedded in a robot able to analyse text, voice, faces, images beyond numbers. An example of this technology is the Lowebot, able to scan the code of a product held by a customer or hear directly by him the product name. Then it confirms if the product is present in the store and eventually go to pick up the item, thanks to its indoor navigation capabilities.

5) Data Virtuoso and 6) Robot Expert

The last two AI forms are Data Virtuoso and Robot Expert. The former is the digital form, while the latter is the robot form. Both can analyse numbers, text, voice, faces, images. These forms present the highest grade of context awareness, the ability to adapt to each situation and find answers by learning from the circumstances. Full context awareness is still premature. A 2016 survey distributed to AI researchers finds that respondents assign a 50% chance that high-level machine intelligence will be developed around 2040-2050, with the probability rising to 90% by 2075.

Task automation: technologies, deployed currently or to be deployed

Context awareness: technologies that *may* be deployed in the long term

	Digital form	Robot form
Analyse numbers	*1 – Controller of numerical Data* Ex: Karnetix	*3 – Numerical Data Robot* Ex: Cafè X
Analyse text, voice, faces, images	*2 – Controller of Data* Ex: Stitch Fix	*4 – Data Robot* Ex: Lowebot
Analyse numbers, text, voice, faces, image	*5 – Data Virtuoso*	*6 – Robot Expert*

Figure 11: AI framework. Source: Davenport (2020).

1.2.3 Marketing automation

Marketing automation means automating the marketing actions to show relevant and interesting communications to our users, thus improving the performance of the dimensions of interest (Franceschini, 2020). The metrics a business wants to improve depend on which stage of the customer journey it is focusing on. For example, the metrics may be lead generation, customer conversion, customer retention[1].

The first to introduce the term marketing automation was John D.C. Little in a presentation of 2001. According to him, the motivation for adopting marketing automation has been to find an adequate response to the huge amounts of data that are collected. The idea was to improve the current operations of the company by adjusting its offer (e.g. price, promotions, web design) through the collected data of consumers.

The diffusion of AI has opened numerous possibilities of application for marketing automation. AI allows marketing applications to carry out many activities without human intervention, such as: collecting information on consumers with tracking tools, conversing with their customers, offering personalized content according to customer characteristics.

However, the primary objective of marketing automation is to offer content personalization based on acquisition and navigation behaviour. A simple example can be a website that personalizes its design according to the gender of the user that opens it. The automation can find out the user gender from the data he has provided to Google and modify the web design accordingly. For instance, the software can assign colours tending to pink for women while blue for men.

The principal advantages of marketing automation are the following (Franceschini, 2020):

- time-saving: the possibility to save the time of workers for repetitive tasks and exploit the time saved to focus on the definition of the marketing automation strategy.

- higher engagement: consumers enjoy products personalized on their characteristics, therefore they will be more inclined to interact with the brand and purchase.

- better performance: the possibility to increase the performance of dimensions such as revenues, marginality, or metrics like the number of interactions with a particular call to action. The choice will be done accordingly to the company parameters of interest.

[1] Lead generation rate: total number of leads generated, divided by the total number of visitors through a particular channel (source: Single Grain). A lead is any person who indicates interest in a company's product or service in some way. A lead is generated when the company gets information from a user to establish a successive commercial interaction.
Lead conversion rate: percentage of leads who make a purchase and become clients.
Customer retention rate: percentage of clients who have not left the firm considering a certain period of time.

But can marketing automation tools be considered AI? Paragraph 1.1 shows that AI can be divided into two macro types: weak or strong AI. Nowadays, most adopted marketing automation instruments employ a rule-based system, thus a weak AI. A rule-based system consists of a logical program that uses pre-defined rules to make deductions and choices to perform automated actions (ThinkAutomation). Hence applications of this type use a set of answers set in advance by AI specialists to respond to the problems to which they are addressed. The logic of the program is that if X happens, then it executes Y. For instance, tools like email automation, dynamic content personalization, push notification usually work in this way. Considering email automation, most of the time, it functions that the automation sends a flow of emails when the user subscribes to the newsletter or perform some type of call to action. In the most elaborate cases, the emails will be personalized according to the user characteristics.
However, most complex marketing automation tools may even involve strong AI by adopting machine learning and deep learning algorithms. These intelligence forms can autonomously learn the best way to solve a problem without following the strict predefined commands of a rule-based system. Chatbots built through machine learning may be an example. These are not limited to replying to already established inputs from which the user chooses with default answers, but they can understand open questions and give more personalized responses. Moreover, they learn from past interactions according to the feedback received and adjust their answers for future conversations.

When to adopt marketing automation

Before implementing marketing automation, a firm has to consider some factors. Otherwise, the firm will incur significant costs without getting a significant return from the investment. The firm has to evaluate the following points (Franceschini, 2020):

- The presence of a clear value proposition. It is important to consider that adopting marketing automation could be of great support for the development of the company, but first of all, the firm should have a clear marketing strategy. It means knowing which customers the firm wants to serve and where it can find them. Once the firm has selected the target consumer, it has to deeply analyse his characteristics and offer them the right automation to satisfy his needs.

- The business manages categories of products and targets very different. Automation can be useful for setting the appropriate funnel for each type of customer, as very different consumer targets require a personalized sales strategy. The same is for a shop selling many categories of items.

- Some of the business products are sold by recurrent purchases. In this case, automation can be helpful since it allows to save time for an action that has to be repeated across time. An example could be the automation of a monthly coffee capsule acquisition process.

- UI platform well optimized. Automation can be useful only once the firm has already a well-optimized platform with which can interact with its consumers. For example, this implies a website quick to navigate and an interface optimized to offer a great user experience along all the touchpoints with its clients.

- The firm has already a good level of traffic stream on its platforms. A high number of visitors allows the company to make segments more relevant because it has collected more data and can extrapolate some traits shared between groups of customers. Moreover, with a large number of users, the firm can scale up the benefits of marketing automation and return faster from the investment made. However, even a start-up may decide to run marketing automation from the start of the business to deliver a better customer experience.

Customer journey

To effectively implement marketing automation within the company operations, the firm has first to have clear the customer journey of its business. The customer journey is defined as the set of experiences that a customer has during the time spent between the various touchpoints of the customer journey (Lemon & Verhoef, 2016). Once companies know the different touchpoints, they can implement the appropriate automation to optimize their customer experience. Lemon & Verhoef (2016) point out three stages through which customer journey can be conceptualized:

- Prepurchase: phase in which the consumer recognizes a need and considers the possibility of satisfying it with a purchase. The customer behaviours belonging to this stage are the need recognition, the consideration of whether to satisfy the need and the search for the product that can fulfil this desire. Previous experiences incise in the choice of which brand to consider.

- Purchase: the stage that covers all customer interaction with the brand and its environment during the purchase itself. The customer behaviours belonging to this stage are the choice of product, the ordering and its payment.

- Post-purchase: the stage covering the customer interaction with the brand after the purchase. The customer behaviours belonging to this stage are the usage and consumption of the product/service, the post-purchase engagement and the service requests. Reaching customer satisfaction at this stage is essential because it allows triggering a loyalty cycle that will lead the customer to buy back the products of this brand since the user experience has been satisfactory (Edelman & Singer, 2015). Furthermore, a satisfied customer will not repeat all the considerations made the first time to decide which product to buy among the different brands but will go straight to the brand he felt satisfied with. In this way, the classic customer journey is reduced, thanks to the bond established between the customer and the firm (fig.12).

Offering a high customer experience during the different touchpoints is very important for the firm because a satisfied customer will be the best promoter of the brand. Businesses need to focus heavily on the existing customer to offer them the best experience rather than trying to reach new customers. According to various researches, a customer with a bad experience shares it among 9 to 15 acquaintances (Mastella, 2020). Moreover, it is about 7 times more expensive to acquire a new customer than reconvert an existing one, and the probability to sell to an existing user is much higher (60-70% compared to 5-20%). 81% of buyers trust their families' and friends' recommendations more than companies' business advice (Redbord, 2018). Relating the online, 76% of users regularly use online reviews to determine which business to rely on (Mastella, 2020). The data point out the importance to offer a great experience to customers because once they will be satisfied with the service, they will contribute to finding new clients for the firm. Word of mouth has a great impact to convert new prospects.
Nowadays, customers can easily research and compare products, therefore firms have to be reactive to engage customer interest and differentiate themselves from competitors. Businesses should lead rather than follow customers on their digital journey, finding and optimizing touchpoints where they can offer them a compelling experience.

Tools of marketing automation can serve this scope, by offering each customer a personalized path to enter in contact with the brand and smoothing the purchase process of products and services.

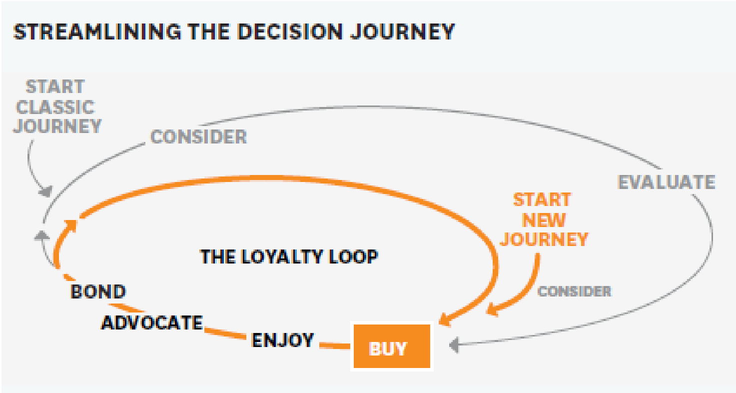


Figure 12. :Representation of the consumer journey. If the consumer very appreciates a firm product, he can enter in a loyalty loop that eliminate the evaluation step, as he trust and love the firm products and does not need to consider other brands. Source: (Edelman & Singer, 2015)

A useful customer journey map that helps companies identify how they should behave along the various stages of the customer journey is provided by HubSpot's adaptation of the Flywheel model developed by James Watt.

In this model is placed at the first position the alignment between customer satisfaction and firm success. Indeed, satisfied customers will share their positive experiences with other people and consequently, they attract new potential clients. The concept behind flywheel is "*With the flywheel, you use the momentum of your happy customers to drive referrals and repeat sales*" (Hubspot). The model is constituted of three phases: attract, engage, delight.

Attract

The phase where the firm has to draw the attention of its target audience. During this phase, people are searching for solutions to their doubts, information, opinions. The objective for the firm is to remove doubts and overcome the barrier that separates people from trying firm products. An attracting strategy is the creation and publication of content - such as blog articles, content offers, social media – that provide value and information to the audience. Important is to attract the attention of people, not force it, otherwise people will be disappointed and avoid the firm initiatives. To optimize the process is recommended to apply SEO strategy. SEO stays for search engine optimization and are all the techniques used to maximize the opportunity to gain organic traffic from search engines (Fortin, 2021).

Engage

In this phase, people know they have a problem and are searching for a solution. Firms have to show they can offer this solution through their products and services. Firms have to make aware consumers that they are the best solution to choose by establishing a dialogue with them that may lead to a long-term relationship. The firm has to be able to share what the business can provide to users across all the different touchpoints through which relates. Besides showing the features and advantages of their offer, firms should show their stories and anecdotes to create empathy with the audience.

Moreover, the firm should have clear it is selling solutions rather than products because consumers are interested in what the product may offer, not the product itself.

Delight

Delighting strategies concern the activities the firm take to make the customers happy, satisfied and supported after they make a purchase. The objective is to get them to make another purchase and share their customer experience. For this reason, the firm members have to work to guarantee assistance and consultancy to consumers at any time they may need support. Instruments like chatbots and surveys can help at this scope. Chatbots may help to assist 24/24 for recurrent problems. They may also inform consumers of new opportunities by which they may take benefit, and help them install these new offers. Surveys are useful to collect consumers feedback after a period they have used the firm product. Then, the firm can use the information gathered to improve the current services.

Even social media listening is an important means to listen to consumers questions and feedback. Responding to arising consumers doubts and comments will make them feel valued for the firm. Consumers delighted with the purchase experience contribute to attracting other potential clients by sharing how they felt good with the firm. Indeed, the flywheel is a circular model with three stages – attract, engage and delight – connected, with the last stage contributing to the success of the first (fig.13).

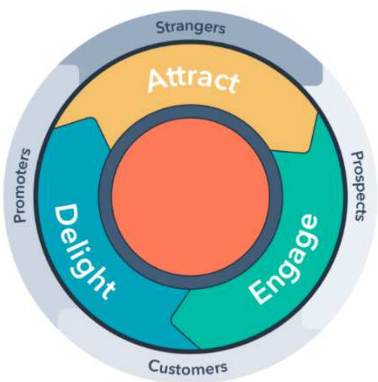


Figure 13: the Flywheel model. The phase of delight is related to the attract phase in a circular process.

Funnel

To make the customer journey engaging, the firm has to set up a specific sale funnel to make the product offer attractive and the experience compelling. Funnel means the set of automatic processes that come in succession, aimed at maximizing the value given to customers and consequently the value they give back (Mastella, 2020). The value can be brought in different forms: it can be given through the product or service, helping customers save time for certain activities or simply establishing a relationship with the consumer. A funnel is the set of processes the firm has planned to interact with the desired customer to offer him the highest value and at the same time capture the maximum value he can give back. The funnel objective is to create an optimized system able to acquire and reconvert a user more times. The concept behind the creation of a funnel is not to recover from the investment from the first transaction with the user, but through multiple transactions with the same customer. The purpose is reached by setting a relation with the customer.

A typical design funnel may involve the following phases: reach the designed customer, bait him, convert him (persuade him to buy), cross-selling, reconversion. However, the funnel design can change accordingly to the product sold, the objective the company wants to reach, the typology of the customer, and many other factors.

It is a concept often associated with digital marketing, but a funnel can be found in every sale process, both online and offline. It is the path that the customer must take because the company could reach its set goal. A simple example of a digital sale funnel could be that of a user who sees an advertisement, clicks on it, goes to the sales page and buys the company's product.

Marketing automation tools allow setting up personalized funnels to reach the desired audience, with modest costs.

The best outcome for a firm is to create a funnel chain. Funnel chain means the unique flow that qualifies and segments the users and autonomously conduces them in the appropriate funnel, at the right moment (Mastella, 2020).

The five steps a firm should take to design a successful funnel are (Vignali, 2017; Mastella, 2020):

1. *Definition of the product-market fit*

The firm has to find a market segment where it can become a leader. To reach this goal, it has to differentiate from the competitors and choose a market niche yet to be explored. It has to identify which consumer it wants to serve, identifying itself with the consumer mindset to think

in the same way and recognise their needs. It has to understand which steps the consumer has to take to fulfil his needs.
In particular, the firm should focus to draw "true fans". It is a terminology coined by Kevin Kelly in 2008 and refers to the very affectioned customers that are available to follow every project of the firm. They are customers with high potential, as they repeatedly buy from the firm and are the first promoters of the brand. They will share their good experience with the brand and convince other users to buy products by word of mouth.
Moreover, the firm has to analyse its possible competitors and understand which of their processes are successful and can be assimilated.

2. *Acquisition and qualification of users*

The company must acquire users and convert the traffic of users it attracts into the traffic of users it owns. For example, it can attract users to the website through an advertising campaign, and from there try to collect the contact of the user. The contact will serve to communicate with users through channels the firm owns like the email channel, WhatsApp, the Facebook group, Facebook messenger, the phone number. An effective way to collect the user contact is by the adoption of a lead magnet. A lead magnet is a free product that is given in exchange for the user contact. For example, it may be a free e-book downloadable once the user adds his email.
Then the firm has to understand which is the best moment to propose an offer to sell. An offer proposed too early may fail as the user does not know deeply the company value and therefore will ignore the offer.
Before the firm proposes its offers, it first should show its value and inspire trust in customers. A solution may be to give to potential clients something as proof of the quality of the firm. What it can use is the "tripwire", an offer with low cost but high perceived value. The user has to perceive the tripwire as an affair to be grasped. Although the cost may be minimal, it should not be free, because if the user buys the product, he will be qualified as ready to buy successive offers from the firm. An example could be Sky which offers its Sky Q bundle at only 9€ for the first month. This process will help to identify the consumers that are very interested in what the firm has to give and those who are not. It allows to start a relationship with the interested users and convey them in future profitable transactions.

3. *Disruption of the belief system*

The price of a product is determined by the value a user assigns to it and the brand selling it. If the firm can create a relationship with the clients, the value assigned to the product can significantly increase. Therefore the firm has to communicate with customers its philosophy and its story to instil empathy in them. Communication should be reciprocal, involving the customer in an engaging dialogue through which to understand what are his interests.
Once the company has collected the user's email in step two, it should start communicating with the user. It can be done through a sequence of emails, in which the company tells its story, its values and some of its most significant anecdotes. Considering a sequence of 5 emails, the first 4 will share the values and the history of the firm to create empathy with the audience. The last email will incorporate a small survey in which some questions will be asked to collect the interests of users and allow the firm to send customized offers proposed in the future. The users who answer the survey will be the people already interested in the firm. Therefore the firm will be able to segment its users and convey them in the appropriate funnel of the funnel chain, corresponding to their interests. Others not responding to the questionnaire, are not interested yet, and the company has to find another way to gather their interests. The process of capturing the interest of these latter will be explained in step five.

4. *Conversion and maximization of the profits*

Once the firm has recognized the customer in line with its proposal and has shared its values with him, it can start to convert its audience and sell its products. To maximize profits and the value it offers to its consumers, the sale firm offer should not limit to the front-end offer. It may include strategies such as back-end offers, cross-selling, up-selling, down-selling. A front end offer is an offer visible to all users, regardless of previous purchases. Instead, a backend offer is the offer activated immediately after purchase. Cross-selling is the sales strategy consisting in offering additional products or services related to products previously acquired by customers or those in which they have expressed interest. Upselling is a strategy consisting to persuade clients to buy the high-value version of a product instead of the version they were originally thinking to buy. For instance, a seller may offer his client a discount on the premium version of the product he is interested in, to persuade him to buy the high-quality version. Down selling is a strategy consisting in propose to clients a lower value version of a product instead of the version they were originally thinking to buy. For example, when a buyer decides to stop buying a product he was interested in because the price is too high, the seller could propose a cheaper version of the product and be able to close the transaction. All these strategies are profitable because they rely on offering products related to those in which the consumer has already shown interest. However, they have to be adopted according to the appropriate context.

5. *Nurturing, segmentation and reconversion*

Fundamental phase to make a chain funnel. As already mentioned, a chain funnel is a set of various funnels, to which customers are addressed according to the most appropriate for their characteristics. The chain funnel accompanies the customer from the first contact with the business to his loyalty and continuous reconversion. Marketing automation allows this cycle to run autonomously and continuously. The fifth phase aims to segment also the customers that in the third phase has not interacted with the firm. It is possible through a sequence of emails sent to users involving different topics. Each of the emails will incorporate one or more in-depth links to give more information about the topic treated in the email. If the user will open one of these emails and click on the link, he will receive a tag that labels him as interested in this argument. From this moment, a new sequence of emails will be sent based on the topic of which the user has shown interest by clicking on the link. The user will be also ready to receive offers regarding this preference.
The process illustrated allows the firm to segment all its audience, also the part that has not answered the survey mentioned in the third phase. Now, the firm can know what may interest its users, provide each of them the contents of his interest and exclude other contents, not in line with the subject of interest for the users.

The five steps presented (fig.14) are an example of an effective funnel, but they are not to be necessarily taken as they are and used by all businesses. Each business has its attributes and may focus also on some of the steps, according to its strategy. However, if the process may differ, the important are the concepts behind the various actions.

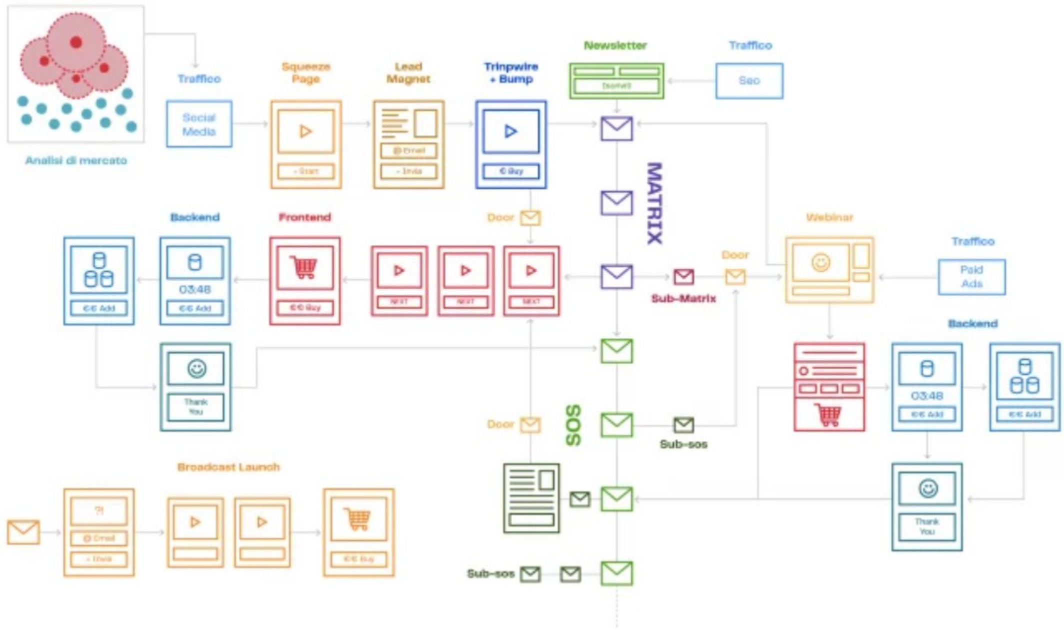


Figure 14.: Illustration of a digital sale funnel. It starts with a market analysis to identify the potential customers the firm wants to reach. Through advertising and social media, the users are lead to a squeeze page (destination page created to persuade users to subscribe to the newsletter). To persuade users to subscribe, the firm can use a lead magnet, a free content donates in exchange for the email. So to identify users ready to buy, a tripwire is proposed, a product with a low price but high value. If the user buys the tripwire means that he will be inclined to acquire successive products of the firm. From there, the firm can send a sequence of emails of presentations with one having a survey asking the user interests. According to the survey answers given (if it was carried out by the user) and the link clicked in the emails, the firm can understand user interest and send personalized offers. Source: Vignali (2017).

Tools of marketing automation

Several processes can be used to automate marketing functions. Some of the most relevant are presented below (Franceschini, 2020):

Email one to one

It is an email whose content, graphic design and offer are personalized according to the customer segment to which it is sent. A typical example could be the email of the abandoned carrel, an email remembering the articles which are been added in the carrel but whose purchase has not been completed. Other examples could be the birthday email with a discount on some product; the email for those who do not acquire for more of a certain period; the email searching to sell some product correlated to a previous purchase.

This typology of email may present several advantages. The offer included in the email may have much relevance for the consumer, as it may be based on the past product of interest. Or could be signal a particular moment for the customer (e.g. the birthday), making feeling him important for the company. Or could act as a reminder for the consumer, since it is from much time he has not acquired anything, and showing him an offer may trigger the desire to repurchase some products. Given the relevance for the consumer, email one to one usually have a higher open and interaction rate.

Dynamic products recommendation

They are insertions where are displayed personalized recommendations of products. For example, the recommendation can be based on recently viewed products, similar past purchases, products correlated to acquired items, products most purchased from other users. Usually, the recommending product display could be placed on the homepage of the website or during the acquisition phase of other products. An interesting strategy used by some firms is to suggest, in the carrel, some complementary products that combine with what the user is buying. For instance, if the user is buying a pot, the recommendation might be the offer of a cover (fig.15). The advantage of a dynamic recommendation product is to personalize the acquisition user experience, by offering a product that could be of interest to each particular customer. Furthermore, this strategy allows companies to cross-sell and up-sell their products, offering value to their customer and at the same time making a high profit.

Fig.15 : example of cross-selling strategy through dynamic product recommendation. A cover is showed in the carrel, as complementary product to buy together with the pot. Source: www.learnn.com.

Popup, Bottom bar

They are web windows that show contents in real-time on the webpage visited by the customer, according to the user behaviour. A popup may appear when the user enters a webpage and take up a large part of the screen, while a bottom bar is less invasive and appears in a bar at the

bottom of the page visited. Usually, they comprise some discount to apply in the next purchase. A typical example may be a discount offered to a new user whether he subscribed to the newsletter of the firm. The user should have the discount to apply already in the emails, but if they forget to have it, the popup/bottom bar acts as a reminder of the discount.
But the content may be various: for instance, to a loyal customer that has made numerous purchases in the past, an invitation to an event (e.g. a competition with prizes on social networks) may be more appropriate than a discount, since it makes feel special a customer who does not need an economic stimulus to make a purchase.
Like the previous tools, they allow to personalize the buying experience and can hook a new user into making the first purchase.

Dynamic modification of contents

There are marketing automation software allowing to change the display of web content based on certain conditions. This possibility opens a lot of new opportunities to offer a personalized experience to users. For instance, if the user is recognized as male or female, the website can change its look to take an aspect more pleasant to the specific gender (e.g. changing the colours or the product visualized on the homepage). But the personalization can take into consideration a lot of aspects: if the user is married, if he has sons, if he has a pet, the age, etc. Dynamic modification of content permits to show more advantageous offers to new users compared to existing customers. Moreover, it allows optimizing the campaign of advertisement, since it allows to make coherent the advertisement announce shown in the search view page with the content visualized in the website.

Fig.16: the home page of the website changes the title according to whether the user has typed the word "crocchette", "mangime", "ingrosso" in the search engine. In this way the user who opens an ad will see perfect consistency between what he is looking for and what the website offers. Source: www.learnn.com

Push notification and chatbot

Push notifications allow sending personalized communication according to the typology of the customer and the location of him, with its previous consensus. An example could be when a customer in the proximity of a store where he has often bought, receives a notification on his phone to inform him of a special promotion. There are also web push notifications, so in this case, the message is displayed on the desktop. An example of a web push notification could be a notification that appears on the shop's website, with a discount on a product that the user has seen many times in that period.
A chatbot is a software designed to simulate a human conversation via text chat, voice commands, or both (Investopedia, 2020). They allow sending personalized interactions with users through platforms like Messenger. They are powerful instruments, as they permit to have more engaging conversation tailored to the information of the user. For instance, if the chatbot is integrated with Messenger, the user with which interact will have to access Facebook. Therefore the chatbot will exploit the information shared by the Facebook profile to customize the interaction. Recently, chatbots are also integrating with SMS and WhatsApp, opening the possibility to have a contact till more direct with users. Chatbots can have many applications: an example could be the possibility to order simply by interacting with the bot. The argument will be deeply discussed in chapter 2.

How to use marketing automation during the customer journey

Following are presented some marketing automation actions that can be adopted in the different phases of the customer journey (Franceschini & Poli, 2021). The actions are contextualized in the Flywheel customer journey model.

Attract

- Personalized banner: for the new users, firms can display on their website a banner with a product discount for the next purchase that is made available after they have subscribed to the newsletter.
  For users that have arrived on the company website by clicking on an advertisement about a particular product, the firm can personalize the customer experience by showing for this category of users a discount on the category of the product shown in the banner. Therefore the firm can offer a targeted discount on the product of interest and ignore all the other categories of product the firm may have in inventory.

- Website personalization: for new users, firms can opt to insert in the head of the homepage elements of social proof – as positive customers review and the partners that already work with the firm – to instil trust in them.
  Moreover, for the new users, the homepage can show the most popular products as there is not a record of the past searches.

Engage

- Welcome emails and nurturing emails: for the new users who have just subscribed newsletter, the firm can send a sequence of emails of presentation in which it can tell the story of the firm, the problems it has overcome, some anecdotes regards the firm. This information will contribute to engaging users and establishing a relationship. After the first descriptive emails, the firm can start to propose offers and surveys to collect user information and personalize successive proposals.

- Personalized banner: for instance, for users that have already made some purchases, the firm can display a banner with the new entry products when the user opens the firm website.
- Push notification for abandoned carts: companies can send a message to ask customers if they want to complete the purchase since they have left the cart abandoned.

- Website personalization: for existing customers, the homepage can display the products they have seen in the past search or products related to past purchases.

- Chatbot: company websites can show chatbot assistance when a user has made several visits to a page of a product, without he has completed the purchase.

Delight

- The birthday email: recurrent email sent to customers on the occasion of their birthday. Generally, the email has attached some sort of "present" such as a discount for a product.

- Email workflow for VIP users: after a certain number of emails, the company can consider a customer as particularly valuable for the firm. To this category, the firm can send reserved offers to make them feel special.

- Push notification with reserved offers: the same as the precedent point but through push notifications.

- Assistance chatbot: the company can make available a chatbot to assist customers with recurrent problems and doubts they incur after they have bought a product of the firm.

1.2.4 Recommendation systems

Data collection

Nowadays, firms can widely adopt AI to recommend the most suitable products and content for their customers. Firsts, firms have to understand the needs and preferences of their customers. It happens through user profiling. Customer profiling could be defined as the description of a customer, or set of customers, that includes demographic, geographic, and psychographic characteristics, as well as buying patterns, creditworthiness, and purchase history (Monaro, 2021). Applying AI, firms can collect users' data and build models that can predict users' preferences, attitudes and interests (Monaro, 2021). The data collected are based on two different types of information: explicit information and implicit information.

With explicit information, people are directly asked to express themselves about their attitudes, thoughts, feelings and behaviours. Examples could be the likes on social media, reviews on Amazon, the compilation of surveys about product satisfaction or questioners about their psychophysical traits.

Instead, with implicit information firms collect data without requiring users to directly report a subjective evaluation on the dimension of interest. However, these data could be analysed to extrapolate an evaluation of the interest dimension. Examples could be text analysis, face reading, eye tracking, physiological index, brain reading. Specifically, some practical applications could be: eyes tracking that scan the pupil dilation of people to infer the interest level for a product displayed on the firm website; the text analysis of comments on social networks to infer the sentiment analysis toward certain themes, like politics or brand popularity; the analysis of facial expressions to infer in real time the emotions of people, and offer personalized products for the moment.

The collection of implicit information reveals particularly useful when customers do not express their opinion clearly or they do not know what they want (Monaro, 2021). It happens because people may not want to disclose some information or because they are not aware of them. For example, at the question –"how many cigarettes do you smoke daily?"- people frequently may underestimate the real number because they illude themselves that it is not so bad as it is. It is a mechanism of self-deception that may divert firms from collecting the right information.

Find consumer preferences based on personal data collected by AI

Once firms have collected customer personal information thanks to the adoption of AI technologies, they can effectively offer tailored products to their clients. In their study on "The Big Five and Brand Personality" (2009), Casidy, Tsarenko and Anderson find that customer personality dimensions are significantly related to particular dimensions of brand personality. In fig.17, the results of the study are summarized: each brand personality is linked with the correspondent personality dimension is expected to find in users choosing the brand.
In fig.18, the results are categorised for gender.

Brand personality	Characteristics	Corresponding Big Five dimension
Trusted brand	Trustful, Reliable and Persevering	Conscientiousness
Sociable brand	Creative, Friendly and Outgoing	Neuroticism, Openness and Agreeableness
Exciting brand	Active, Adventurous and Cool	Extroversion
Sincere brand	Simple and Caring	Agreeableness

Figure 17: brand personality dimensions.

Brand personality	Corresponding Big Five personality	
	Male	Female
Trusted brand	Neuroticism	Conscientiousness
Sociable brand	Extroversion	Openness to Experience
Exciting brand	Extroversion	None
Sincere brand	Openness to Experience	Extroversion

Figure 18: gender differences in brand personality.

Firms may consider these correspondences to start making the first sort of personalization offer and understand which type of customers are more profitable to serve.
Then, companies can use AI to understand the personality of customers. Youyou, Kosinski and Stillwell (2015) compare humans and computers accuracy in evaluating people personalities of a sample of volunteers.
To assess the accuracy of the personality assessment, the estimations of people and computers were compared with the participants' self-assessment on the Big Five Personality test. The test measures the traits of openness, conscientiousness, extraversion, agreeableness and neuroticism of the respondents. The level of self-other agreement was determined by correlating

participants' scores with the judgement made by humans and computer models. Self-other agreement self-other agreement refers to the similarity between personality descriptions by the self and by others.

To gauge the human accuracy, the personality of the participants were evaluated by acquaintances filling the Big Five Personality test. Among the acquaintances considered, there were work colleagues, cohabitants, friends, family members and spouses of the participants.

Instead, machines to establish the participants' personalities take their likes from Facebook profiles to build a linear regression model for the five personality traits (fig.19). The computer's average accuracy was computed on the average number of likes per individual, equal to 227.

The more are the number of likes, the more the person reveals his qualities improving the computer accuracy prediction (fig.20). The results were that the computer's average accuracy (r=0.56) is significantly better than that of an average human judge (r=049) and similar to that of the spouse (r=0.58).

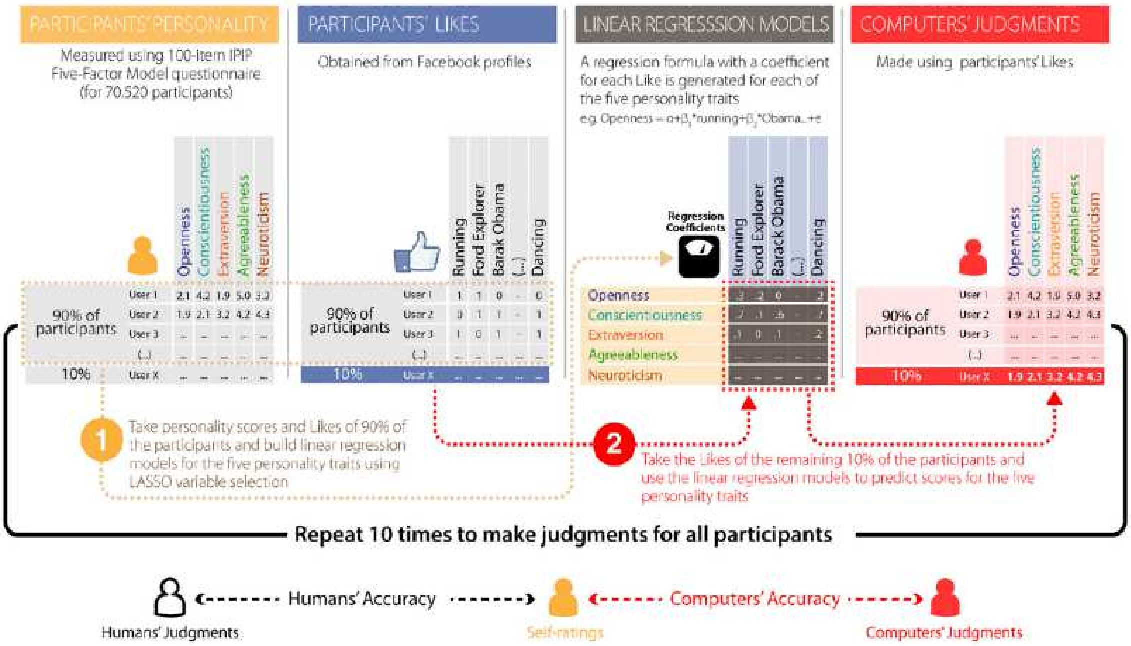


Figure 19: methodology used to obtain computer-based judgments and estimate the self-other agreement. Participants and their Likes are represented as a matrix, where entries are set to 1 if there exists an association between a participant and a Like and 0 otherwise (second panel).
The matrix is used to fit five LASSO linear regression models , one for each self-rated Big Five personality trait (third panel). A 10-fold cross-validation is applied to avoid overfitting: the sample is randomly divided into 10 equal-sized subsets; 9 subsets are used to train the model (step 1), which is then applied to the remaining subset to predict the personality score (step 2). This procedure is repeated 10 times to predict personality for the entire sample.
The models are built on participants having at least 20 Likes. To estimate the accuracy achievable with less than 20 Likes, we applied the regression models to random subsets of 1–19 Likes for all participants. Source: Youyou (2014).

The better performance of computers in predicting personality could be attributed to two factors: computers can store a huge amount of data to consider in prediction; computers through statistical models can avoid motivational biases that affect human judgement.

However, one of the limitations of the study is that considers only the personality dimensions represented on the Big Five personality test. The human personality has many other aspects, and human judgement could be better to describe many small facets of human behaviour that are not easily grasped by a machine.

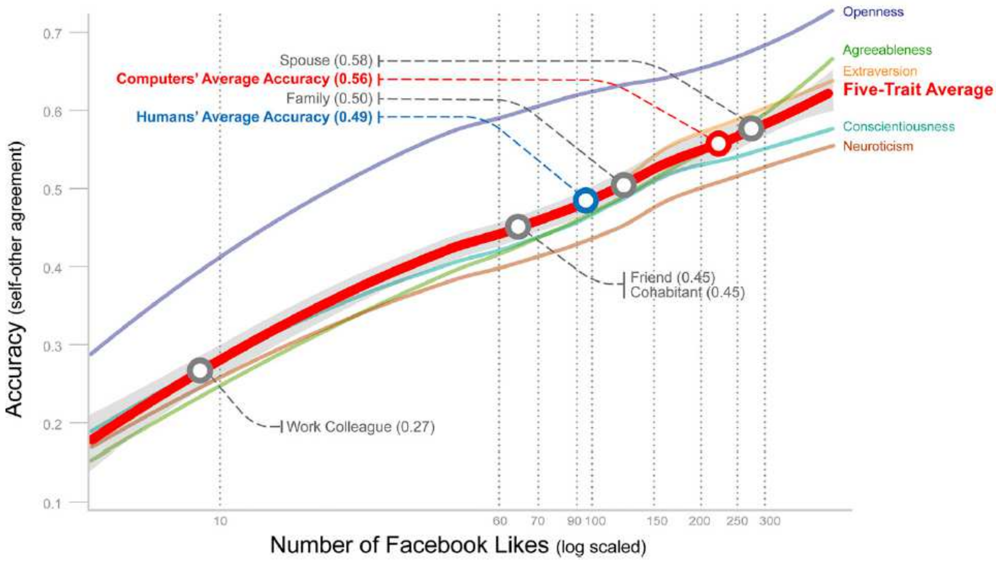


Figure 20:. more are the number of Facebook likes on which the AI software can base its prediction, more will be its accuracy. Taking into account the average number of likes - equal to 227 – of the participants, the accuracy prediction of AI was just found out significant better of the Humans' average accuracy.

1.3 The pitfalls of AI adoption

The adoption of AI in marketing is not the pill for fulfilling all the problems. Indeed, the technology presents several limitations that push firms adopting AI to be aware of the implications and stay focused to avoid them.
The limits can be analysed from different perspectives. Puntoni et al. (2021) point out four customer experiences that are affected by AI adoption. They are the AI data capture experience, the AI classification experience, the AI delegation experience, the AI social experience. Experiences are negatively affected when customers perceive exploitation, misunderstanding, replacement, alienation from the interaction with the AI.
The AI limits could be originated from several motivations among which: the lack of common sense of AI, the lack of transparency (par. 1.3.2), the lack of competence and frustration generated from job replacement (par. 1.3.5).
These bad perceptions will be found in the next paragraphs where common AI pitfalls are analysed in detail.

1.3.1 Biases

The customer experience might be negatively affected by biases on the AI algorithm, thus inducing them to abandon the use of AI and share the disappointment with other people.
It could happen when AI classifies consumers to a wrong group or when AI made biased predictions based on group assignment (Puntoni et al., 2021).

The causes of an unfair prediction could be biased dataset training or the result of endogeneity (De Bruyne et al., 2020). An example of a biased prediction is shown in a recent case published in the Harvard Law Review (2017). In the case, Wisconsin court charged Eric Loomis with five criminal counts related to a drive-by shooting. The sentence evaluation was supported by AI software to assess the risk of recidivism. The assessment of the software was based on both information coming from an interview with the offender and the offender’s criminal history. The question that emerged was if the software could make biased predictions against the race of the offender. Indeed, Angwin et al.(2016) proved that some risk assessment tools adopted by courts wrongly predicted black defendants to re-offend at a rate nearly twice of white defendants.

The researchers showed that after the termination of the sentence, white defendants, judged low-risky by the machine, actually fall again on crime more often than the riskier black ones. The cause of the wrong prediction is the biased training dataset from which the software learns. For instance, in America, black prisoners convicted of murder are frequently more likely to be innocent than their counterparts. Therefore the convictions historical dataset of murder will be biased against race since there are recorded a lot of black people wrongly accused of murder. The software is based on past convictions and since it computes the probability of being convicted of recidivism and not recidivism per se, historical data are racially biased.

One could argue that the software algorithm does not take into account the race in the prediction but if this is formally true, instead, the software can understand from secondary data (e.g. income, school attended, geographical location, profession) that defenders are from the black race and penalize them in predictions.

Other forms of biases can be found in social biases. For instance, an AI image recognition software finds it more difficult to recognize an Indian bride, confusing her for a "performance art and costume" (Zou and Schiebinger, 2018). It happens because AI software often is trained on image datasets formed mainly by pictures of the United States, even though they have only 4% of the world's population. In this way, the software has a lot of labelled examples to recognize a bride dressed in white, but very few to identify a bride dressed according to different cultures. Fig.21 shows the image composition of ImageNet, one of the datasets most adopted by deep neural networks for image classification.

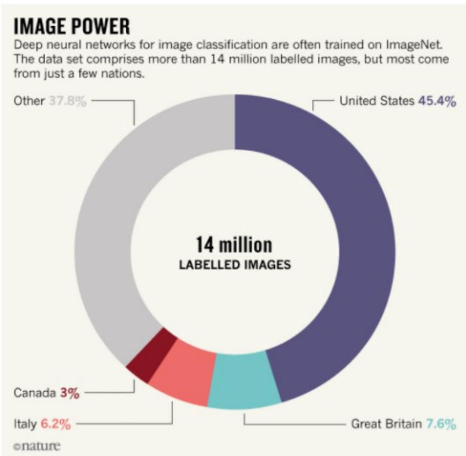


Figure. 21: graphic showing the origin of the country of the images belonging to Image Net. Source: Zou & Schiebinger (2018).

For similar reasons, AI software could be biased against gender. For instance, some activities are more frequently associated with a specific gender. If the supporting dataset associates a lot of images with a particular gender, the AI software could result biased in recognizing the gender of the agent involved in the task. Zhao et al. (2017) show as in the ImSitu dataset adopted, the cooking activity is over 33% more likely to involve females than males, and the trained model applied for visual recognition amplifies the exiting dataset bias further (Fig.22).

In a marketing context, this could be translated into biased prediction toward certain categories of customers. Companies can use AI software to make price discrimination according to the category of customers upfront. For example, Ayres and Siegelman have shown (1995) that in new car dealerships, dealers quoted a significantly lower price to white males than to black or female buyers. A possible explanation was that dealers apply discrimination on price based on statistical inferences about consumers' reservation prices. However, the data analysed in the research do not sustain this theory.

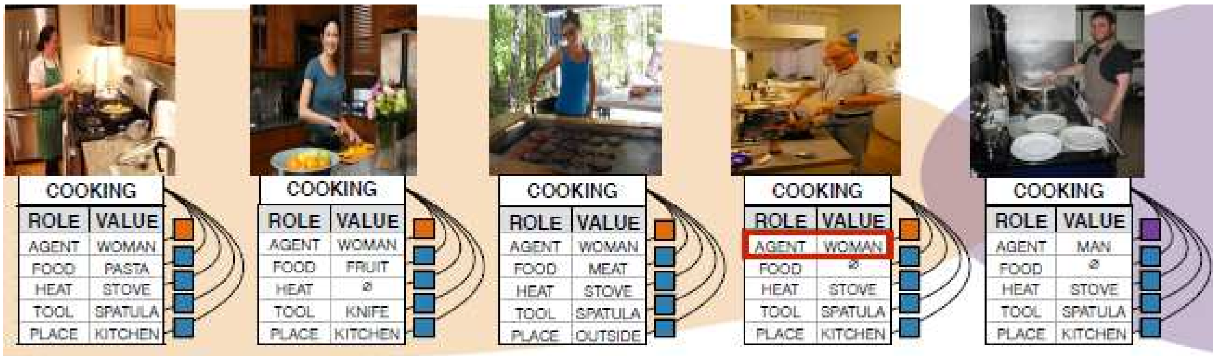


Figure. 22: AI machine can fails in recognize a male cooking, because it is trained to associate females in cooking activities. Source: Zhao et al. (2017).

Hence, AI software should not rely on these data since they are biased against women and black people, and there is no evidence of an economic theory of price discrimination to justify the different treatment, besides a possible gender and racial prejudice.

The other cause of bias is endogeneity (De Bruyne et al., 2020). Endogeneity happens when a statistical model employs variables that are itself explained by other variables present in the same models. The phenomena may verify when the data selected to run a model are not casually chosen but picked up according to discretion. For instance, it is the case of a firm that wants to deploy an AI algorithm to calculate the likelihood that a customer targeted by an advertisement will buy a product, but the firm's marketing manager choose to target the most receptive customer at that time instead to select it randomly. In this way, the AI model might underestimate the probability that an inactive customer makes a purchase.

Endogeneity can also be triggered by the company management reacting in a way that reinforces the prediction of the AI model. For instance, if the model predicts as less profitable a category of customer, the management may think to give less focus to these consumers, that receiving lower attentions, will buy less from the company. The future predictions of the model will further highlight the less profitability of these customers, because of the management behaviour and a self-prophecy fulfilling will happen. A vicious cycle is set by making biased AI predictions (De Bruyne et al., 2020). For this reason is very important to build reliable models, where there is transparency over the results.

1.3.2 Explainability of Artificial Intelligence

"Machines are beneficial to the extent that their actions can be expected to achieve our objectives"(Russel, 2019). One of the main limits of AI is that often complex deep learning algorithms have outputs that people do not totally understand. Indeed, even if machine learning starts to learn from a provided dataset, the articulated set of successive iterations make it increasingly more difficult for data scientists to follow the calculations the machine is doing to get its results. Companies need control over their algorithm if they want to exploit the insight that they can generate. For instance, they have to know why their AI algorithm has predicted some new market trends so to understand if the prediction could make sense. More simply, also consumers may want to know the reason for a particular suggestion or product recommendation by the AI. Ribeiro, Singh and Guestrin (2016) give a meaningful example of how an AI model could be misleading in its interpretation.
A neural network was assigned to differentiate between a photo of wolves and a photo of dogs. While the results were very accurate, the process adopted in recognition was not reliable. Indeed, the researcher found AI basing the discrimination on the photo environment, since wolves are usually on snow, while dogs are on grass. This is a spurious correlation, therefore not indicating a causal relation, that could lead to bad interpretations and take wrong strategies. Considering a marketing context, not understanding the reasons behind AI predictions could lead to biased results and wrong strategies.

As the term "machine learning" says, the machine itself learns how to achieve an objective. In supervised learning, the learning process is assisted by a data scientist that provides a training dataset in which the data are already labelled and the output is well defined. Instead, in unsupervised learning, the algorithm has not this support and has to find alone some pattern in data, in order to classify them. This approach fits well when it is not clear the output wanted in advance and the machine works to find remarkable relations among data. Unsupervised learning complicates the understanding of data scientists about the AI results since the algorithm has wide freedom to operate.

A trade-off between prediction and explainability could be pointed out among machine learning models. Data scientists have to choose if to adopt an algorithm with a reasonable restrict number of internal components, but providing transparency in their decision making, or a very complex deep learning algorithm that learns from itself the relevant features to use (Rai, 2020). In the latter case, the model sacrifices transparency and interpretability for prediction accuracy. In Fig.23 Rai classifies four different explainable AI (XAI) techniques, according to two dimensions: (i) whether the technique is model-specific or model-agnostic and (ii) whether the technique is designed to provide an explanation that is global in scope to the model or one that is local in scope to a prediction. Model-specific techniques use interpretability constraints within the model to make it clear, while model-agnostic techniques use the inputs and predictions of the model to find explanations over the results.

	Model-specific	Model-agnostic
Global	Enforce interpretability constraints into the structure and learning mechanisms of deep learning models	Develop interpretable global surrogate models based on input-output associations predicted by a black-box model Apply diagnostic techniques to understand the importance of specific features in a black-box model's predictions
Local	Use attention mechanisms to show how the model selectively focuses on features in high-dimensional input for an instance	Develop interpretable surrogate models with local fidelity in the vicinity of an instance

Figure 23: Classification of XAI techniques. Source: Rai (2020).

Having fully explainable models is very important to gain the trust of consumers and overcame the barrier of diffidence that may separate them from the AI adoption. Consumers knowing how the AI comes to certain decisions can make it more reliable in their eyes.
The lack of common sense of AI amplifies the need for control and transparency. What may appear clear to human people is not to machines. For this reason, companies in its adoption have to specify with very attention the algorithms to implement to avoid unexpected consequences.

1.3.3 Privacy

Privacy can be defined as the right to control information about ourselves (DesJardins, 2014) and privacy violation occurs when personal information is used without the consensus of the data owner. The theme becomes relevant for AI-enabled products, given the large quantity of data they can gather from customers. The data collected allow firms to make future predictions and offer personalized products to consumers. Products like fitness trackers, Alexa, social networks, websites have all access to a vast selection of information, that users more or less consciously concede.

Consumers balance two aspects in evaluating if giving access to their data. One negative aspect is relative to the disclosure of sensitive information to external entities; the other positive is relative to the possibility to receive a more personalized offer, tailored to own characteristics.
Therefore, companies to breach the diffidence of customers have to make consumers aware of the benefits that the disclosure of personal information can give in terms of product/service customization. Firms have to be clear on how the data collected will be used, otherwise, consumers do not leave data when the uncertainty is high (Walker, 2016).
In particular, three privacy-enhancing factors may nudge the consumer to disclose personal data (Martin and Murphy, 2016; Du & Xie, 2020):

- Trust: firm efforts to enhance trust promotes positive marketing outcomes, that include consumer wiliness to disclose. In contrast, efforts to reduce privacy concerns could be counterproductive (Wirtz and Lwin, 2009). A way to generate trust could be providing clear and easy to understand communications about firm privacy policies, thus making transparent to the consumer how their data are used.

- Personalization or some other benefits: consumers are more willing to disclose their information if they envisage a personalization of the offer. Other benefits that could promote disclosure include access to free services, streamlined customer-company interactions, and financial compensation.

- Control: the possibility to control own personal privacy settings enhance the wiliness to disclose. However, privacy settings have to be set in a way that simply allows consumers to choose their preferences, otherwise, an overload of choices and options could decrease the effective control over data and trigger feelings of frustration and exploitation. Therefore, firms have to choose an architecture that reduces the cognitive efforts required to set privacy preferences.

Problems arise when customers feel exploited by companies, in a way that perceives abuse over their privacy. This could happen for several motivations (Puntoni et al., 2021): intrusive methodologies of data acquisition that are difficult to avoid; little clarity on how consumer information is aggregated over time and across contexts; lack of transparency and accountability of data collector. Puntoni et al. (2021) point out three psychological consequences of data exploitation: negative affect, moral outrage, psychological reactance.
Firms to avoid these drawbacks have to emphatically listen to consumers that have experienced exploitation in AI data capture experience and search to adjust privacy settings according to the more sensitive categories of customers. Significant is the negative experience of Leila, a sex worker who kept his identity hidden on Facebook but was shocked to find some of her regular clients among the "people whom you may know" function on Facebook (Hill, 2017).

1.3.4 Alienation

In a social meaning, alienation is the state of being withdrawn or isolated from the objective world, as through indifference or disaffection (Wordreference). This negative feeling can be amplified by the large adoption of AI-enabled products in society, as most of them cannot perceive human emotions and respond to them accordingly. As a result, interaction with AI devices such as chatbots could be perceived as "detached" and lacking empathy.

Puntoni et al. (2021) point out two main types of alienation triggered by an inadequate AI social experience. The first occurs in any kind of failed interaction between machines and customers, for example, due to the machine's lack of empathy. It can result in the machine giving answers totally out of the appropriate context, hurting the user's sensitivity.
The second type refers to the failure to interact successfully with particular groups of customers. For example, they could be people with disabilities or with some health problem, who in the situation of interacting with hospitals, could feel annoyed in sharing sensitive information with an AI technology like a chatbot.
One way to mitigate this problem is to customize the chatbot's interaction with users, such as calling users by name. Furthermore, companies should allow users to switch from chatbots to human representatives when the situation becomes difficult and sensitive.

Also, alienation could be generated by racial and sexist questions/comments made by people to bots, to which they respond with condescension or other discriminatory phrases. An example is what involves Tay, a Microsoft chatbot that employed artificial intelligence to interact with millennials on Twitter (Tennery & Cherelus, 2016). Microsoft shut it down after just one day of activity because it learned to produce offensive posts after users negatively influenced the chatbot by pestering it with racist and sexist comments. Fig. 24 represents an example of Tay's inappropriate response to a provocative question posted by a user.

1.3.5 People replacement

According to a study by the OECD (2018), across the 32 countries included in the OECD group, close to one in two jobs are likely to be significantly affected by automation, based on the tasks they involve. Generally, poorer countries will be more affected than the richer and the organisation structure will play an important role in the possibility to be automated (e.g. manufacturing has more chance to be automated compared to the service industry). Looking at each task, about 14% of the jobs in OECD are highly automatable, with a probability of over 70%; another 32% of jobs have a probability between 50 and 70% to be significantly affected by automation in the way they are carried out.

Figure 24. Example of an inappropriate answer of the AI chatbot Tay to a question made by a user. Source: The Guardian, 2016.

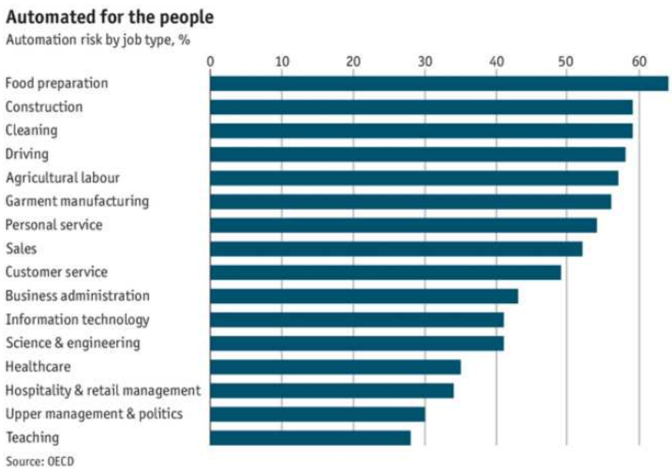


Figure 25. Probability to be affected by automation for each job. Source: The Economist (2018).

However, society must look to AI not only as a substitute for the worker but also as a means of supporting different job positions and as a creator of new job positions. Workers will have to continually revise their skills to combine their knowledge with the new possibilities offered by the arrival of AI. At the same time, the presence of AI could be stressful for workers for several reasons. Puntoni et al. (2021) point out three threats:

- The desire of people to attribute consumption outcomes to one's abilities and efforts. People like the accomplishment related to the execution of their tasks and may look at the AI tools as something that without effort can do better of them and get the merits resulting from a good job. Desiring to preserve their pride, workers may tend to attribute to themselves the good results coming from their job and blame the AI for the negative outcomes. In addition, some categories of works might be more reluctant to adopt AI, since its use could prejudice the job identity.

- The paradox of automation. The concept means that relieving workers from simple tasks that could be smoothly assigned to machines, may deplete workers of the basic skills necessary to grow in their work position that prepare them to complete more complex ones (De Bruyn et al., 2020).

- Loss of self-efficacy, caused by an excessive dependence on the capabilities of AI, can lead users not to make the most of their possibilities.

It is worth noting that the concepts analysed must be seen both from the point of view of a professional who looks to AI as a support/replacement tool for his work and from the part of a consumer who in his experience of using a product adopt the AI. For instance, a consumer may be felt "constrained" if AI results too intrusive in recommending products that might be to his liking, without giving the partial chance to refine the selection according to the current preferences. Indeed, people can have multiple preferences, which evolve over time, and an algorithm that only suggests products based on past preferences can be limited.
Puntoni et al. (2021) highlighted some actions companies could undertake to avoid the risk people felt threatened by AI:

- Collaborate with experts and people involved in jobs or more general situations affected by AI to understand the consequences of human replacement.

- Understand which activities people prefer to keep for themselves and which others delegate to AI. Moreover, understanding which activities are more intrinsically devoted to humans, because require abilities such as creativity that machines have more difficulty replicating.

- Offer the possibility to people to modify the forecasts of AI, even slightly, to overcome the aversion against the adoption of AI. Dietvorst, Simmons & Massey (2018) show that the preference for modifiable algorithms was the desire for some control over the outcomes, and is enough also a slight possibility of modification to make the people more satisfied with the forecasting process.

1.3.6 Difficulties in transferring tacit knowledge from humans to machines

AI applications can be successfully applied in most situations where they base their learning algorithm on explicit knowledge. Explicit knowledge refers to knowledge that is relatively easy to articulate and communicate and then transfer between people (Lee & Yang, 2002). It resides on formulae, textbooks, technical documents since it is clearly codifiable. On the other side, tacit knowledge is difficult to transfer to machines.

Tacit knowledge is related to things that we know but are difficult to tell, as could be for the knowledge of skills that are learned by doing and experience (Polany, 1962). Tacit knowledge cannot be fully expressed even by an expert and can only be transferred from one person to another through a long period of apprenticeship (Polany, 1962). A classic example is the ability to ride a bike. It is possible to explain the coordination of movements to keep the balance on the bike, but only by attempting a boy will learn the correct movement pattern.

Considering marketing, tacit knowledge plays an important role to generate positive results (De Bruyn et al., 2020). Indeed, casual ambiguity may permeate the company history successes, thus making it difficult to establish the relation between the causes and the positive marketing outcomes.

Tacit knowledge can arise from the complex coordination among the company functions through the exchange of formal and informal information. Also, employees can be a great source of tacit knowledge that is realized with years of experience made by trials and errors in the operational field. All this knowledge can hardly be transferred to machines, as it is not clearly codable in an algorithm.

Indeed, the transfer of tacit knowledge relies mostly on the gain of experience and the collection of information embedded in emotions (Nonaka, 1994), and AI applications should internalize this way of learning to have full access to knowledge.

The transfer of knowledge must be mutual (De Bruyn et al., 2020): the machine has to learn from the expertise of people, but people also have to understand what machines may have learned from their calculus. Constant and deep focus on the machine work will be central to identifying and adjusting possible biased results, obtaining clarity on the AI output and thus getting a higher acceptance of the AI adoption by people.
People trust AI if they are aware to be in control over its operation and know what it is under the "black box".

Chapter 2

Chatbots

2.1 Chatbot overview

AI chatbots are computer programs that simulate human conversations through voice commands or text chats and serve as virtual assistants to users (Luo et al., 2019).

The first chatbot to be built was ELIZA in 1966 by Joseph Weizenbaum. The researcher designed the program in a way that can imitate a human conversation. The chatbot responded to questions and statements of the interlocutor according to a predefined script, similar to that of a psychotherapist (Onlim, 2021). The algorithm could match the word the user enters with a list of possible responses.

From ELIZA, chatbots are significantly evolved by integrating new functionalities and becoming more intelligent. Today, chatbots can be applied to numerous situations. For instance, they can answer real-time users questions about doubts and problems arising from the product/service offered by a company. Besides the information part, chatbots can be beneficial for quickly collecting customer orders. An example is Domino's Pizza which allows the ordering of pizzas simply by sending a pizza emoji to the number provided. In this way, both the customer and the company take advantage: the customer can quickly put an order without waiting in a possible queue; the company can save personnel employed on receiving telephone orders and focus on pizza preparation and home delivery.

Firms may seriously consider the adoption of chatbots in their business. The market statistics are clear: in 2020, the market was worth $17.17 billion, and analysts project it will reach $102.29 billion by 2026. Moreover, chatbots popularity is increasing (Jassova, 2021). Nearly 40% of internet users worldwide prefer interacting with chatbots over virtual agents (Insider, 2021). Insider Intelligence predicts (2021) that AI could automate up to 73% of healthcare administrative tasks, and the adoption of chatbots could save the healthcare, banking and retail sectors $11 billion annually by 2023.

2.1 The economic impact of chatbots

Firms should consider costs and benefits before implementing a chatbot. Intelligence Partner (2020) points out six economic advantages of chatbots for companies:

- 24/7 availability at low expenses. Unlike human staff, chatbots can be present at any time of the day to interact with users without additional costs. Indeed, the charge of a chatbot is independent of the time when the firm used it, while human employees can require overtime labour costs for working on night shifts or at weekends.

- Increased value in customer satisfaction. Chatbots can do the same or even better than human agents for basic tasks. Employees can be affected by several circumstances like the mood of the day, physical conditions, the surrounding environment that can alter the work performance. Instead, chatbots can offer standard qualitative answers to the most common enquiries and guarantee customers fulfilment.

- Increase in satisfaction of the agents and improvement in resource allocation. Delegating standard and repetitive tasks to chatbots allow employees to focus on the most challenging assignments. In this way, they can exploit their full capacities for the jobs requiring creativity and a personalized contribution. It permits to increase the productivity of the agents and their motivation. Consequently, the staff turnover rate may drop with all the costs associated with the assumption of new employees. The result will be a reduction of the work expenses and an improvement of the working environment that could enhance the quality of the service.

- Reduction in operational costs. Chatbots reduce the number of calls, emails, messages on social networks received and sent by human staff. Chatbots can ease the workload and limit the distractions of employees by lowering the emails and calls they receive that may interrupt their workflow. Therefore, workers can dedicate specific hours to control enquiries that were delegated to the chatbot automation in the meantime.
  This point is related to the precedent as staff will experience more productivity. However, also chatbots need to be monitored to avoid problems and miscommunication with users. The observation could be necessary mainly at the beginning phase of the chatbot implementation to examine whether the interactions with users are adequate. Also, if the company adopts a machine learning chatbot, the interactions improve with time as the chatbot learns from past situations. Thus, over time, the reliability of the chatbot increases, reducing the need for attention. A way to efficiently control the chatbot is to adopt a feedback system. It allows users to rate just happened interactions thus letting the staff focus on conversations that had problems.

- Reduction in labour costs. Chatbots can do part of the employees' work, thus lowering the request for personnel and saving much money. The use of a chatbot results increasingly advantageous with the growth of the number of contacts to manage. Usually, the price of a chatbot is fixed in classes depending on the number of users connected, but it is less than proportional to the addition of contacts. Hence, for economies of scale, the increase of contacts reduces the unit cost per contact. Nevertheless, chatbots can substitute people only for the most common and simple tasks. Therefore, companies should allow users to contact staff by chatbots if they need assistance.

- Boost of revenues. Beyond substituting humans in assisting users, chatbots are great also to support the marketing function. For instance, they can collect customer information, orders and conduct surveys on the company products.

A case study of the benefits and costs of a chatbot implementation comes from the study of Forrester Consulting. IBM (2020) commissioned the consulting firm to examine the potential return of investment a company may realize by deploying Watson Assistant.
Forrester developed a composite organization representative of four companies that have adopted the IBM Watson Assistant. Then, it estimated the economic effects that the IBM chatbot adoption could generate on the composite organization. The predictions are estimated considering the data collected from the four companies that compose the organization. Forrester examined a forecast period of three years and actualized the results at the present value (yearly discount rate of 10%). The composite organization has the following characteristics: revenue: $10 billion; geography: headquartered in Europe with worldwide operations; employees: 40,000; monthly conversations: 1 million (12 million annual).

Fig. 26 shows the quantified benefit resulting from the chatbot implementation to the composite firm.

Containment represents the number of conversations answered satisfactorily without human intervention. In computing the total customer conversation containment savings, Forrester considered that: the IBM assistant is devoted to reply only to a part of the aggregate annual conversations of 12 mln; the effective rate for Watson response; the cost difference between staff response ($6.00 estimated) and automated response ($0.50 estimated); a risk factor adjusting downward the savings obtained by 20%. Forrester considers that IBM can increase the number of conversations covered effectively over time, thanks to the machine learning process. The result was a containment saving of about $13 mln over three years at present value.

Total Benefits						
REF.	BENEFIT	YEAR 1	YEAR 2	YEAR 3	TOTAL	PRESENT VALUE
Atr	Customer conversation containment savings	$1,584,000	$4,989,600	$9,900,000	$16,473,600	$13,001,653
Btr	Consolidation of internal help desk, IT, and HR agents	$0	$2,040,000	$2,040,000	$4,080,000	$3,218,633
Ctr	Increased efficiency from agent assist	$0	$0	$1,350,000	$1,350,000	$1,014,275
Dtr	Correct conversation routing savings	$2,276,640	$2,656,080	$3,225,240	$8,157,960	$6,687,951
	Total benefits (risk-adjusted)	$3,860,640	$9,685,680	$16,515,240	$30,061,560	$23,922,512

Figure 26: Total quantified benefits associated with the adoption of the IBM Watson Assistant. The last column shows the present value at year 0 of the total benefits. Source: Forrester (2020). https://ibm.co/3q6UFKt.

The IBM assistant can provide also support to employees for technology issues and assistance for human resources questions. The IBM chatbot offers two benefits. The first is that the chatbot is a widespread assistant that helps workers and collects data about them. The second is that the chatbot saves HR personnel because they can do part of their work. In addition, human resources can reallocate some workers to more suitable job positions through the information collected by the chatbot on the employees. The result was an actualized economic benefit of about $3,22 mln.

The IBM chatbot can assist agents and increase their efficiency. In companies like financial service organizations, often agents have to interface with the internal help desk to ask for information. It could happen while they are on a call with clients so that they have to place them on hold. The effect was several calls to manage for the internal call centre and a waste of time for the customer. A chatbot can interact in real-time with the agent and provide the information he needs about the client, thus leading to an improved customer and working experience. Forrester considered that this chatbot application is activated only from the third year and estimated its present value at about $1 mln.

The IBM chatbot can offer significant help to route customers with problems to the correct staff assistance. Without the preliminary customer categorization, the user may ask for the incorrect assistant for help, thus leading to a loss of time for both. To estimate the conversation routing savings, Forrester considered the percentage of conversations misrouted before Watson; the saving from resolving a correctly routed call rather than a conversation requiring transfer; the transfer success rate of Watson. Forrester estimated the correct conversation routing savings over three years at about $6,7 mln at present value.

Total quantified benefits over three years were almost $24 mln.

Then Forrester mentioned a list of unquantified benefits of adopting IBM Watson, even if it did not quantify them for the study. Following some of these benefits are cited.
Watson can offer a competitive advantage over competitors. Employees become happier as the chatbot does the most repetitive tasks. Companies can integrate Watson into all their different digital channels, like mobile apps, social media messaging apps and websites. In this way, users can interact with the company through their preferred channel. The IBM chatbot can serve customers at every moment of the year. In particular, it can offer a quick way to interact with customers from another country who have a different time zone and without the need for nighttime shifts. The IBM assistant can limit the need for additional hiring. Indeed, existing staff can handle additional capacity with the support of the chatbot. Finally, Watson enhances brand awareness for companies adopting it, and customers will see them as tech leaders.

Subsequently, Forrester estimated the costs. Figure 27 shows the expense items.

Total Costs

REF.	COST	INITIAL	YEAR 1	YEAR 2	YEAR 3	TOTAL	PRESENT VALUE
Etr	IBM licenses	$0	$20,700	$80,213	$138,000	$238,913	$188,791
Ftr	Internal labor costs	$124,200	$93,150	$62,100	$62,100	$341,550	$306,861
Gtr	Conversation analysts	$742,500	$742,500	$1,485,000	$2,227,500	$5,197,500	$4,318,326
Htr	Professional services fees	$287,500	$120,750	$208,150	$121,900	$738,300	$660,883
	Total costs (risk-adjusted)	$1,154,200	$977,100	$1,835,463	$2,549,500	$6,516,263	$5,474,861

Figure 0-17: Total estimated costs associated with the adoption of the IBM Watson Assistant. The last column shows the present value at year 0 of the total costs. Source: Forrester (2020). https://ibm.co/3q6UFKt.

IBM license costs over three years amount to about $5,5 mln at PV. The composite organization pays $0.0025 per message.

Internal labour costs over three years amount to about $5,5 mln at PV. The item consists of the payments to engineers to implement the chatbot system.

The composite organizations had to employ conversational analysts to improve the answers of the IBM chatbot and consequently the containment rates and the customer experience. The firm can reassign some existing agents or hire new staff to get conversational analysts. The total costs estimated over the three years are about $4,3 mln and are attributable to the salary of the new positions required.

The composite organization pays for the professional services of IBM both for implementation and on an ongoing basis. The organization needs the assistance of IBM to integrate the chatbot system into its business and to trainee its employees to use effectively it. These costs should increasingly decrease as the organization gains experience with the new tool. Forrester forecasted a three year total PV of about $4,3 mln.

Figure 28 shows the Forrester estimation of the economic impact of the IBM chatbot adoption over the composite organization. The outcome is positive. The investment yields net benefits of about $23,5 mln at present value. The organization can pay back the initial investment of $1,15 mln in six months. The ROI forecasted is 337%.

Cash Flow Table (Risk-Adjusted)

	INITIAL	YEAR 1	YEAR 2	YEAR 3	TOTAL	PRESENT VALUE
Total costs	($1,154,200)	($977,100)	($1,835,463)	($2,549,500)	($6,516,263)	($5,474,861)
Total benefits	$0	$3,860,640	$9,685,680	$16,515,240	$30,061,560	$23,922,512
Net benefits	($1,154,200)	$2,883,540	$7,850,218	$13,965,740	$23,545,298	$18,447,651
ROI						337%
Payback period						< 6 months

Figure 28: Net benefits from the IBM chatbot investment estimated by Forrester Consulting. Source: Forrester (2020). https://ibm.co/3q6UFKt.

2.1 Conversational marketing

Chatbots are an optimal tool by which firms can engage customers through conversational marketing, an approach based on the conversation between customer and company. With this approach, a firm can establish a unique dialogue with the clientele, creating a personalized relation one-to-one. Conversational marketing can enhance the brand value in a period in which consumers give high importance to customization and the experience perceived. The value-added of conversational marketing is to create an emotion and a unique experience for the client. Moreover, chatbots can solve current customer problems and provide a wealth of data to improve the company products.

Conversational marketing can close brands to customers, helping to humanize them (Roy and Naidoo, 2021). When a brand focuses on a personalized dialogue strategy, it generates empathy, breaking down the imaginary barrier that divides customers and companies. It happens through answering client questions, helping him, giving purchase advice, following him during his customer journey.

The three pillars on which conversational marketing rests are (Banfi, 2021):

- Envelopment: through the interaction with the customer, the brand can create an experience that goes over the single purchase. It generates a relation among the parts that make the client feels part of the brand. The customer will continue to follow the brand, becoming loyal to a brand he appreciates.

- Understanding: interacting with the customer allows brands to understand his needs and tailor a real-time answer. The customer will appreciate the attention and the consideration he received, increasing the chances he acquires a brand product.

- Advice: customers will positively evaluate advice on the buying decision in addition to the simple answer to questions. A chatbot able to offer personalized recommendations on what items could optimally fulfil the customer necessity allows improving his purchasing experience. Today, companies with large databases about client characteristics can know pretty well which product can satisfy their clients. For instance, Sephora proposes surveys to customers to understand their profiles and give tailored suggestions on which product could be ideal for their physical characteristics (Forbes, 2016).

2.2 Typologies of chatbots

Chatbots can be of different types and can serve different purposes according to the needs of the implementor. In this paragraph, chatbots will be classified for the technology they adopt and for their interaction design. A first evident classification can be based on its mean of communication: only text, only voice, both text and voice.

Beyond that, three principal typologies of chatbots can be identified by starting to consider the technology adopted (Artificial Solutions, 2021):

Linguistic Based (Rule-Based Chatbots)

These types of chatbots use an if-then approach to create conversational flows. Therefore, their flow of messages is highly structured so that each question made by a user can have a predefined answer. The number of conditions to set could be very high to cover all the possible situations. The interaction application may provide users with a limited number of options to simplify the structure and drive them to established personalized flows of messages. At each dialogue stage, the user can select among the options according to his needs. After that, the flow proceeds by providing another assortment of options related to the topic of interest. Automated tests can check the quality of conversation and detects errors to adjust. For example, rule-based chatbots can be appropriated for interactive FAQs, where chatbots answer the questions chosen among the most popular.

Machine learning (AI Chatbots)

These chatbots adopt machine learning algorithms to work. They learn from a training dataset to perform optimal interaction with users. The dataset should be large enough to be relevant and provide a rich assortment of instances that the chatbot can learn. Differently from rule-based chatbots, AI chatbots do not require a predefined answer for each specific case they may face. They do not need that users select among predefined queries. They are suitable for open questions, as they learn from past interactions to improve the current communication and are not limited to the constraint of the rule base system model. They are context-aware as they adapt to the present situation and adjust the interaction accordingly. For these reasons, they are appropriate to engage users through a personalised experience because they are more interactive and give freedom to users to ask questions in their own words.
Interactions with AI chatbots can improve over time as they accumulate experience they exploit to adjust their communication process. Implementing an AI chatbot is complex because many interaction instances could occur, and the chatbot should be reliable in each of them. The chatbot requires a team of AI experts that monitor it and adjust it in case of fallacies. Moreover, a machine-learning algorithm may result in a black box because it is difficult for humans to be fully aware of all the processes executed by the machine. Indeed, in a machine learning

algorithm, the artificial intelligence expert sets the structure with which it operates, but the machine itself finds the optimal way to perform.

Hybrid Model — The Ultimate Chatbot Experience

This chatbot combines both the rule-based and the machine learning models. The advantage of this typology is that it provides at the same time flexibility to users and control over the algorithm. The flexibility allows the machine learning integration to understand a wide range of questions and give personalized answers. Control because it permits to set a rule-based structure in scenarios where ambiguities and problems may arise.

Now, it will be considered the interaction design adopted by a chatbot. According to Folstad et al. (2019), two main typology dimensions address the key characteristics that differentiate current chatbots: the duration of the user relationship with the chatbot (short-term and long-term) and the locus of control for the user interaction with the chatbot (user-driven and chatbot-driven).

Locus of control

- Chatbot-driven: it is a chatbot provided with high predefined interaction design. The script of inputs with which the user can answer and the chatbot can reply is standardized and already defined. In this case, the chatbot controls and drives the conversation. Rule-based chatbots have a chatbot-driven locus of control.

- User-driven: it is a chatbot provided with high flexibility, able to respond to non-predefined questions and give tailored answers. This approach is more engaging for users than the chatbot-driven as it allows a more deep interaction with them. The users drive the conversation as they have the freedom to articulate questions on their terms. AI chatbots have a user-driven locus of control. Examples of user-driven chatbots may be Siri or Google Assistant since a user can articulate any variety of questions without limits by voice.

Duration of relation

- Short-term relation: chatbot of this type does not gather information from the user with which interacts. Therefore the same user that will interact with the chatbot in future receives the same treatment as he would be the first time. The chatbot does not personalize interactions according to past conversations and behaves as they are all are new users.

- Long-term relation: a chatbot of this type collects information from the users it interacts with to provide a personalized relationship over time. It results in more engaging relations that may establish a bond between the user and the brand represented by the chatbot.

According to the dimensions just described, Folstad et al. (2019) have established a framework pointing out four different categories of chatbots (fig. 26).
The crossing of two of the four dimensions identifies each kind of chatbot (user-driven or chatbot-driven locus of control and long-term or short-term duration of relation).

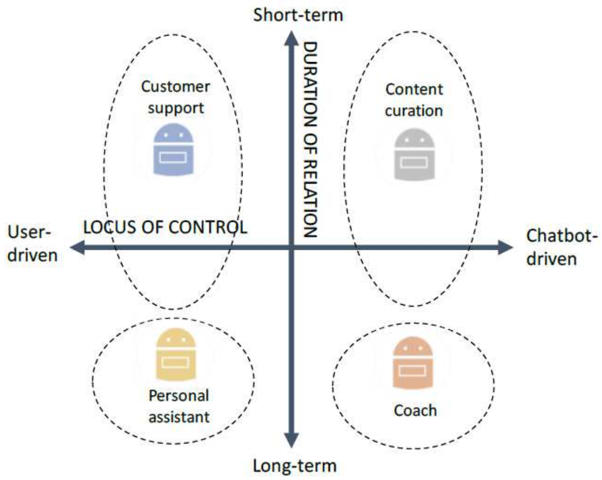


Figure 26 : Typologies of chatbots according to locus of control and duration of relation dimension. Source: Folstad et al. (2019).

Chatbot for customer supports

Generally, it has a user-driven and short-term relation approach. The objective of this chatbot is to identify the user problem and resolve it. The chatbot may have a long-term orientation to relationships when connected to a CRM software that collects users data. Often, designers give the possibility to ask open questions. Then users can give feedback on the response so that the chatbot can adjust successive replies. The chatbot may also provide a list of frequently asked question categories from which the user can choose.

Personal assistant chatbots

They are chatbots designed to serve users through long-term relationships. Similarly to chatbots for customer support, the interaction design aims to ease the entering of questions by users. Often they offer the possibility to ask free questions without limits.
Contrary to the chatbot for customer support, the personal assistant chatbot may be integrated with the surrounding technological ecosystem of the user. An example may be the connection of the Alexa device with the house lighting system to turn on/off the light.
Their objective is to answer users as quickly as possible if the question is sufficiently clear; otherwise, the chatbot can extend the dialogue by asking the user whether it has correctly understood his queries so far. If not, the chatbot can invite him to give other details or explain in other words.

Content curation chatbots

They are chatbots designed to provide content to users, like news, entertainment or other interesting information. They adopt a chatbot-driven approach because they show and suggest available content that the user selects according to his preferences. The user is limited to accepting or rejecting the content provided by the chatbot or filtering it to search for what interests him. Usually, they adopt a short-term relationship with users, not gathering historical information about past interactions. Typically, users interact with content curation chatbots through an options menu without the possibility to ask free questions.

Chatbots for coaching

They are chatbots designed to serve and support users over time. These chatbots can assist users to get new knowledge or reach a specific objective. Generally, there are structured to offer predefined interaction programs according to users purposes. Each session results from the last one to personalize the user experience. However, the interactions of sessions are already scripted, and users have to choose between a limited number of paths.

2.3 Chatbot as a tool to nudge the disclosure of personal information

The chatbot importance to understanding and engaging customers might increase over time. Thomaz et al. (2019) predict that society will experience a shift in the Web nature over the next five to ten years as consumers, firms and regulators become more concerned about privacy. In particular, they argue that users of the standard web will increasingly adopt some of the Dark web tools used to protect privacy. They foresee two types of users will emerge from the web: the Buffs and the Ghosts. The former is the users willing to share their information profiles with marketers. Ghosts, instead, give a high value to their privacy and deny access to personal information. In an environment becoming progressively more privacy-oriented, Thomaz et al. suggest that chatbots could assume a relevant role in nudging consumers to disclose personal data with companies. Chatbots will actively persuade consumers to share personal data to receive tailored recommendations. If consumers perceive these recommendations as highly valuable, they will enjoy sharing their information because they recognize a fair reward in exchange for their data. The personalization paradox describes this concept: the customer trade-off in choosing whether to exchange data for a more tailored offer. Chatbots will be particularly important to nudge sharing personal information of Ghost users since they keep particularly on their privacy.

A way to generate trust in sharing information with chatbots is by anthropomorphism.
If users perceive the chatbot as anthropomorphized, individuals could feel less inhibited when interacting with a computer. They will start to see the machine as more emphatic and near to humans, increasing the perception of trustworthiness and usefulness of AI chatbots.
The anthropomorphism process could consider dimensions as name, gender, embodiment (physical or virtual), the appearance that may include age, ethnicity, attractiveness, personality, tone of voice and the use of some expression. Once consumers perceive that the chatbot has human traits, they subconsciously engage in a conversation similar to what they would have with a human person. They know that chatbots have no real feelings. However, they apply social scripts typically used in human-to-human interactions (Nass & Moon, 2000).

In addition, chatbots can encourage data sharing by the reciprocity norm. For instance, chatbots can start to offer some free useful information first to consumers. The more the customer perceives the information as unexpected and personalized, the more he will want to return some of his data (Cialdini, 1987). The anthropomorphism of chatbots could also contribute to humanizing the target brand, thanks to the possession of social traits (Roy and Naidoo, 2021). Firms can improve the customer experience if users perceive the brand as more human, close to people identity. About this objective, firms have to look to interactions among people to understand the leading social mechanisms. The social judgement literature points out two main dimensions people consider in interpersonal interaction: warmth and competence.

Warmth refers to the quality of being perceived as friendly, caring, empathetic by others. Competence means the quality of being perceived as competent, trustworthy, reliable. It has shown that people extend the same parameters to evaluate non-human entities when they own human-like characteristics (Epley et al., 2007). The concept can apply to firm brands, that with tools like chatbots can make people perceive them as more human. Roy and Naidoo (2021) argue that firms -to enhance the customer experience- have to imbue warmth and competence qualities in their chatbot and relate them to people time orientation. The people time orientation means the timeframe they consider to choose their social behaviour. They examine two people time orientation typologies: present-oriented subjects and future-oriented subjects.

The first category looks to extract the maximum pleasure and reward from the present moment. They are hedonistic as they value instant gratification and the research to live current feelings at best.

Instead, future-oriented people adopt a more rational behaviour for social situations. They can give up social events and instant gratification in the optic of a greater future reward. They think in the long run, looking at future objectives to reach. For example, two students of the two categories may take opposite choices whether to join a social party in the proximity of an exam. Future-oriented students may choose not to go to the party to devote their time studying and getting a good night of sleep. Differently, present-oriented students may decide to go to the party because they value the current satisfaction more, despite the looming exam.

Roy and Naidoo (2021) find that a chatbot interaction with a customer is more effective if the chatbot instils warmth and competence attributes according to people time orientation. They observe that present-oriented subjects are attracted to traits associated with warmth while future-oriented ones to competence. It makes sense as the firsts have a relational focus, and the warmth traits are related to social attributes. Instead, the latter demonstrates responsible behaviour and a task-oriented mindset that fits the competence traits.

Beyond people time orientation, firms have to consider their positioning, the typology of products sold and the context to decide which conversational style to adopt. For instance, regarding the strategic positioning, a non-profit firm may seem more attractive in presenting itself through a warm style than a for-profit firm. Instead, considering the product to sell and the context, a potential buyer looking for a new computer for his work will prefer to interact with a chatbot demonstrating competence. It will inspire trust in the client and ease the transaction.

The considerations made show how companies should consider several factors to create an effective dialogue with customers. Chatbots can help engage consumers, and incorporating traits like warmth and competence can help make them more human and effective in interactions.

However, it is relevant to consider that an excess of anthropomorphism could generate a negative result due to the so-called uncanny valley effect. It consists of the feeling of eeriness and discomfort towards a given medium or technology, frequently appearing in various kinds of human-machine interactions (Ciechanowskia1 et al., 2019).

In their research, Ciechanowskia1 et al. compare the comfort state of people interacting with a chatbot provided with voice and avatar to one with only text. They find participants less pleasant to interact with the former, arguing that this might be due to the failure in imitating a human being. Before the conversation, people had high expectations of the chatbot with avatar and voice, but the hopes were not fully satisfied afterwards. The message is that firms should very accurately design the anthropomorphism of their chatbot if provided because if some of its traits will not seem consistent with the first-hand impression, users will feel disappointed.

Another point by which firms can push self-disclosure is assuring algorithmic fairness and transparency. For instance, certifications relate to the algorithm transparency in terms of the results explainability can ensure that the firm is accountable for the machine prediction. Indeed, this is evidence of the firm commitment to avoid misleading results, heading to biases and wrong conclusions.

To conclude, Ghost and Buff users receive different types of interaction because of their diverse relations with personal data. Ghost consumers will enjoy interactions tailored based on mass personalization, with chatbots having a primary role to engage them in conversations and collect their preferences, needs and prior behaviours. In this way, companies can offer users a more personalized experience with the information got (Thomaz et al., 2019). In contrast, Buff users will enjoy from the beginning of a fully personalized interaction with chatbots since they allow firms to implicitly collect their data and create identifiable profiles based on their historical interactions with the firm (Thomaz et al., 2019).

2.4 Chatbot marketing applications

Chatbots can be applied successfully in numerous marketing applications. Indeed, they can assist users through the different steps of their customer journey. Some of the principal uses are the following (Jassova, 2020):

- Lead generation: phase in which the marketer aims to generate new contacts. Marketers need to convert the traffic they don't own into traffic they possess. The traffic is owned when the marketer can decide where and when to meet him. A classical way to take possession and control over it is by getting the user email. Chatbots are a tool that can help at this scope as they can substitute the traditional online forms in which to add the email. Indeed they have a more friendly-face interface with which the user can establish a more engaging interaction that can lead to the release of the email. The chatbot can even attach a lead magnet in exchange for the user contact to persuade him. As mentioned earlier, a lead magnet is something valuable offered to the user for his data contact.

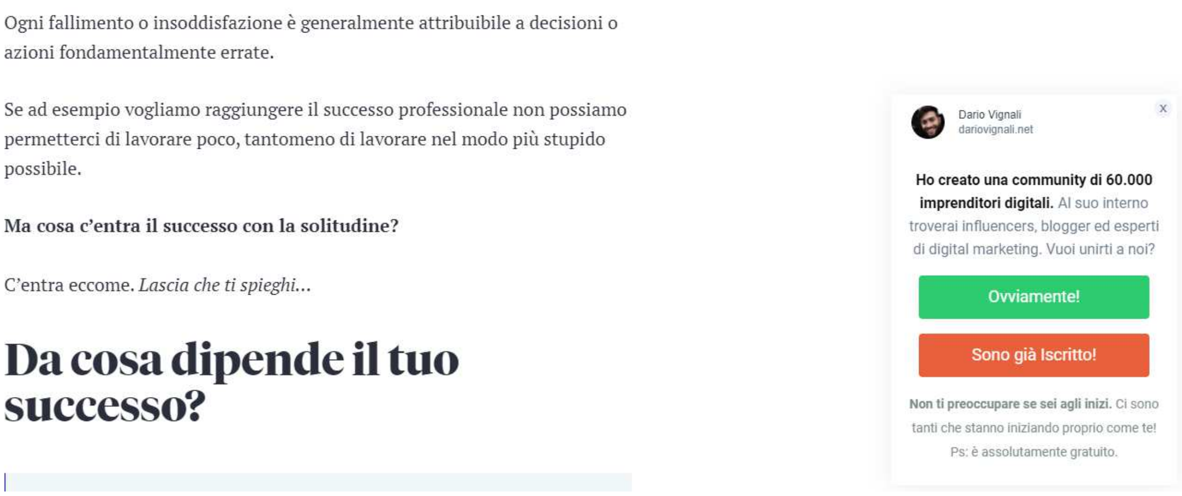


Figure 27 : in this example, the chatbot invites the user to leave his email to join the community and enjoy the information shared within it (lead magnet).

- Lead qualifications: in addition to getting a new lead, marketers may want to have the opportunity to qualify this lead. Lead qualification means grasps from the user enough data to establish a personalized interaction. It allows marketers to understand the people needs and provide solutions appropriate to their situation. If the marketer knows better his prospective client, he can understand how to communicate with him and be more persuasive in his offer. For this purpose, chatbots are an optimal solution because they can engage users in a conversation more enjoyable than a traditional form. Besides collecting the user contact, chatbots can offer a lead magnet to gather some more data about the user. In this case, chatbots may ask for information like the typology of business in which the user is involved, the problem he is searching to address, his budget amount, the number of his employers. Beyond contact information, data of this type allows marketers to segment their users for their qualities and serve them optimally with what they demand.

- Quote generations: a chatbot can be optimal to assist users that need a quote for some product he is interested in buying. Often, users are bothered to call the firm and leave unsolved their doubts, leading to the failure of a possible transaction. A 24/7 chatbot assistant can solve this point by offering users a personalized quote of the product he needs. Moreover, the user will have to give his contact and some of his personal information to have a customized estimate. In this way, the firm gets a new qualified lead, while the user will enjoy giving his data to have a quote.

- Appointment booking and reservations: chatbots are very effective in collecting orders and appointments of users. This way of reservation can be particularly applicable even for small businesses such as a pizzeria. It allows smoothing the workload of calls and avoiding users waiting at the telephone when the line is busy. Instead, users can easily choose the pizza and the delivery time by the chatbot. The chatbot can also be an effective tool for retargeting (Mastella, 2020). For instance, the Messenger chatbot of a pizzeria may ask past clients if they would take a pizza on the occasion of a particular day when people are usually to meet. It may be the day when there is a big football match, and asking people to order in advance can guarantee that their requests will be satisfied, avoiding the risk of not finding the desired delivery time because of the successive high demand. Another possible chatbot application for a pizzeria could be to write to a past client if he wants the same pizza at the same time of the last week and give the possibility to pay with one click if the client has recorded the payment data. It is a quick funnel that allows offering an interaction personalized on the past preferences that hook the client to repeat a purchase. The examples mentioned are that of a pizzeria, but the concepts can apply to several businesses.

- Loyalty programs: businesses can use chatbots to remind in a friendly way about the points accumulated by users with past purchases. Chatbots can induce them to continue buying products from the firm to collect enough loyalty points for some offer of their interest. Or if they have sufficient to apply them to buy a product. Additionally, chatbots can adopt gamification to make the user experience more enjoyable by providing games as quizzes or puzzles to be solved to earn new points.

- Marketing on-site services: chatbots can interact with users to provide information and services about the point of sale. Examples of assistance could be the provision of the business location and opening times, the sending of virtual receipts, the communication of the Wi-Fi password, the sharing of the menu list, the general support about the businesses services and products. Among the advantages of these chatbot services, users can have quick access to information of interest without waiting for the human staff.

- Contests: firms can adopt chatbots to run prize contests to create engagement and fun around the brand and collect users information. For instance, firms can offer contest participation to users who subscribe to the newsletter. In this way, the firm can enhance its brand awareness, and the user will enjoy subscribing to see if he will win. Moreover, the firm can promote the social sharing of user participation to spread further its brand and the excitement linked with the event. A famous example of a contest launched through a WhatsApp chatbot is the initiative of the Vodka Absolut brand (Herianto, 2021). The firm organized an exclusive party for the coming out of the new Limited Edition Absolute Unique collection. Absolute extended the invitation to the event to people who could persuade the virtual chatbot bouncer Sven that they deserved to attend the party. The contest generated a lot of interactions and buzz, arising numerous fun anecdotes about the way people try to convince Sven.

- Reviews: chatbots can be an optimal intermediate to collect feedback about the experience of customers with products or services. A message sent on Messenger or WhatsApp asking for a review can be more visible, quick and pleasant to reply to than a form to complete by email. Also, a chatbot settled in the homepage website of a business can interact with users and show past feedback of customers. In addition, the chatbot can handle customers dissatisfied with the firm services by paying attention and offering assistance. At the same time, the chatbot can explain to new users how the company has handled the negative feedback. In this way, the brand emerges as focused on the sentiments of its clients.

- Community management: to be effective, conversational marketing needs to create an active interaction with all the community members. Chatbots can play a supportive role in communication, especially in numerous communities where the staff may have no time to interact with everyone. For instance, for the community of a company, chatbots can: provide information about the following events as the time or the location; offer news about the company initiatives; share the regulation within the community; answer questions raised by the users.

- Content: companies can use chatbots as a tool of communication to share content with their users. They can implement a chatbot through WhatsApp or Messenger and reach their audience quickly and effectively. Examples of content may be podcast episodes, articles, case studies, the delivery of specific topics requested by a user. In addition, the personalization of the content sent to the user according to his preferences allows to engage him and maintain high the interaction through time.

- Surveys: chatbots can be very effective in performing surveys. They can collect information data more engagingly compared to classical web surveys. Therefore users could be more inclined to disclose data. Moreover, Kim et al. (2019) show as chatbot surveys can generate more accurate responses from users since they recreate the interaction with a human interviewer. Paragraph 3.8 examines in depth this topic.

2.5 The performance of chatbots compared to human sales agents

In their research, Luo et al. (2019) compare the sales performance of chatbots to that of a human sales agent. They tested the sale efficacy by measuring the success of outbound sales calls to sell a promotional deal. They want to study the sales effectiveness of chatbots versus humans by considering how disclosure of the chatbot identity affects the likelihood of a sale. The disclosure happens in different call moments to test how the disclosure timing affects the purchase rate. The objects of comparison were the following:

- Underdogs: they are the least skilled workers in a call centre. Their call reporting performance on sales are in the lower 20th rate over the past six months.

- Proficient workers: they are the best human agents. Their past sales performance are among the top 20th percentile.

- AI chatbots without disclosure: the chatbots do not disclose their identity at any moment during the call.

- AI chatbots with disclosure before conversation: the chatbots immediately reveal their identity at the onset of the conversation.

- AI chatbots with disclosure after the conversation: the chatbots disclose their identity after communicating the promotional deal, but before the customer takes a purchase decision.

- AI chatbots with disclosure after the decision: the chatbot discloses its identity right after customers have decided about the promotional deal.

Figure 28 summarizes the results. Chatbots revealing their identity at the beginning significantly compromised their sales rate, with a dramatic drop of 79.7% compared to the without disclosure condition. However, the purchase rate is similar to the Underdogs (0.048 and 0.049). Chatbots disclosing their identity between the deal conversation and the purchase decision have better performance as the sale rate increases by more than double (0.110) but still lower than the without disclosure condition. Chatbots that reveal identity after the decision, chatbots that do not uncover their identity, and proficient workers have practically the same purchase rate (0.232, 0.237, 0.251). It demonstrates that chatbots can be successful as skilled workers to sell a promotional deal in an outbound sales call. Chatbots that reveal identity after the customer purchase decision have approximately the same performance, as customers remain consistent with the already chosen decision.

The study of Luo et al. (2019) shows that customers have prejudices against chatbots, compromising the deal success. A solution may be to avoid revealing the identity of the chatbot, but it may not be appropriate for ethical reasons. Another possible research finding is to delay the disclosure identity after the conversation with the chatbot so customers might form a good impression in the initial interaction with the virtual assistant (0.110 purchase rate after the initial dialogue vs 0.048 before it). Moreover, the research shows that customers with already experience with AI chatbots could feel less sensible to chatbot disclosure.

Condition	**N**	**Call response rate, %**	**Hang-up rate, %**	**Call length**	**Purchase rate**
Underdogs	1,053	94.96	0.00	39.888	0.049
Proficient workers	1,042	95.97	0.00	63.888	0.251
Without disclosure	1,044	95.79	0.00	64.152	0.237
Before conversation	1,036	96.52	56.30	10.325	0.048
After conversation	1,044	95.78	4.50	63.873	0.110
After decision	1,036	96.52	0.00	63.731	0.232

Figure 28: Chatbot performance under different conditions of identity disclosure compared to more and less qualified human sales agents. Source: Luo et al. (2019).

2.6 Attributes to generate trust in chatbots

As the study of Luo et al.(2019) shows, People generally have discomfort interacting with chatbots. It may be due to a lack of trust, a feeling of being alienated, and keeping not in consideration (Luo et al., 2019; Puntoni et al., 2021). In their research, Przegalinska et al. (2019) study the dynamics of interaction between people and chatbots to find behaviours or communication styles that could lead to discomfort. They suggest three factors that social bots might have to better interact in business and commercial environments. They are:

- Transparency and honesty: chatbot communication is clear and fair, does not lie or embrace deceptive language.

- Predictability: the chatbot acts consistently in line with past experiences, giving people the possibility to know what to expect from the interaction with a chatbot.

- Control and Benevolence: the user (trustor) and the chatbot (trustee) share the same motivations and intents.

These elements highlight the importance of being able to explain what lies behind the output of an AI. Firms need to control their AI and have explainable and transparent algorithms that do not deviate from the users' objectives. Par. 1.3.2. has treated more deeply this argument.

Chapter 3

The chatbot of the Department of Economics and Management “Marco Fanno”

3.1 Structure of the chapter and research questions of the thesis

After the first two chapters regarding an overview of AI and chatbot adoption in marketing, this chapter analysed the application case of the chatbot of the Department of Economics of the University of Padua. This paragraph describes the research questions of the thesis and illustrates the structure of this chapter.
The thesis examines two research questions. The first and main question is:

RQ1: Was the adoption of the chatbot of Economics positive in terms of reduction of the email received (RQ1.1), user satisfaction and potentialities of its features (RQ1.2), and economic impact (RQ1.3)?

For research questions RQ1.1 and RQ1.2, I conducted a questionnaire both through a chatbot surveyor and Google Forms. The comparison of the two modalities allows us to evaluate the other research question topic I investigated: **RQ2: Could a chatbot survey be more effective than the classical web survey distributed with Google Forms?**

The points of discussion of the successive sections with the relative research questions (RQ) are the following:

1. Par. 3.1 gives an overview of the chatbot applications in the university sector.

2. Par. 3.2: the paragraph summarises the purpose of the chatbot of Economics and describes its features and functionalities.

3. Par. 3.3: the paragraph reports the finding of the last report on the chatbot activity between 16-04 to 17-09 2021. It was written by Francesco Ambrosini, one of the chatbot implementors and allows understanding the initial point from which the research on the chatbot of Economics was started (RQ1).

4. Par. 3.4: the paragraph analysed the research question **RQ1.1: Did the chatbot adoption reduce the number of emails tutors received by students?** The hypothesis is that the chatbot should reply to most simple questions, thus limiting the workload of tutors. I considered the number of emails received by tutors because they have to create monthly reports about their activities. Instead, the secretary does not record the number of emails received. The comparison period is 22/04 - 31/07 of the years 2021-2020-2019-2018-2017. 22/04 was when the university staff placed the chatbot on the website homepage. While 31/07 is the last day covered by the tutor's most recent report. Therefore the specific question is: do tutors receive fewer emails in the period 22/04-31/07 of 2021 than the same period of the previous four years?

5. Par. 3.5 analysed research question **RQ1.2: What do students think about the chatbot of Economics? Do they appreciate the chatbot? What function do they like the chatbot could add?** I distributed a questionnaire to students to analyse these questions.

6. Par. 3.6 examinates research question **RQ1.3: What is the economic impact of the chatbot on the Department of Economics?** I estimated the benefits and costs of the chatbot implementation to understand whether the outcome was positive.

7. Par. 3.7 investigates research question **RQ2: Could a chatbot survey be more effective than the classical questionnaire distributed with Google Forms?** I assessed the effectiveness of the survey with the participants' appreciation for the questionnaire and the quality of the responses. I evaluated the quality of answers with the index of differentiation (Pd). A higher Pd value shows that a respondent more strongly differentiates the response options and could be regarded as a lower degree of satisficing (Kim et al., 2019). Satisficing is a decision-making strategy that aims for a satisfactory or adequate result, rather than the optimal solution (Frankefield, 2021).

3.2 Chatbots applications for Universities: state of the art

Nowadays, universities can effectively adopt chatbots for several applications to enhance the communication channel with their students. Even if emails continue to be a great tool to share information, implementing chatbots allows universities to have higher messages visibility and

engagement with students. Emails are often unread and may could too formal and without personalization to engage and create a relationship with students.
Universities may apply chatbots for the following purposes (AdmitHub):

- Admissions: chatbots can alleviate the summer melt among students. Summer melt is the phenomenon for which students between high school and university end up not attending universities because they lack resources, support, guidance and encouragement (Wikipedia). The event happens mainly for private colleges, where the admission taxes can be expensive and poorer students may find it hard to pay them. In the summer period, there is potentially the risk that students do not receive any communication from universities, leading to a loss of contact between the parts and increasing the probability that students will not show up on the first day of class. Chatbots can help with a communication strategy to keep the students in touch with the university, engage them and provide information about possible benefit applications for admission. One example is the University of Wyoming that set up the Cowboy Joe chatbot to increase enrolment and reduce summer melt. The chatbot, provided with a funny personality, interacts with students over the summer, creating a relationship with them. In the first year of the chatbot establishment, the university recorded a 32% drop in summer melt and a 10% enrolment increment.

- Student engagement: chatbots can be of support to create connections among students. They can make students aware of the extra-curricular activities they can participate in, showing them the different possibilities, asking them which one they prefer and finally indicating the next meeting. Thus, they can promote new relationships among students and foster their integration into and around the academic environment. Students engaged in university have a higher probability of success, continuing their studies and ultimately graduating.

- Financial aid: often, the application for financial aid can be complex, leading to students not completing the request and pushing them to drop out of university when the bills are very high. In particular, it may be the case of students coming from low-income families that apply for expensive colleges. Other times, students may not be fully aware of the financial benefits in support of university enrolment. Chatbots can help to simplify the procedure and share information about the different financial aid possibilities. For instance, they can offer information personalized to the student profile, informing him of the benefits he can apply and freeing him from the research burden.

- Community: a coalition of Universities and firms can implement a shared chatbot to stimulate students in continuing their studies by providing information about courses and financial aid. The chatbot can connect students with the work society fabric, addressing them to develop the skills required for the future country workforce. For example, a group of organizations from the K-12, higher education and non-profit fields set up a chatbot to reply to questions about FAFSA (Free Application for Federal Student Aid). While the chatbot is answering students, it can also collect data like names, high school, graduation year to segment users and send timely nudges.

- Serendipity and fun: universities can adopt chatbots to add fun and personality to their image. In this way, they can relate better with students and make it easier to involve them in the university environment. Email can not do the same, since is a more formal communication channel with fewer customization possibilities and without the capacity to interact in real-time. Chatbots can sometimes send pure fun messages or take routine communications usually sent by email and make them feel pleasant. However, chatbots should allow students to adjust the type and frequency of messages received to do not bother students.

3.3 The description and purpose of the chatbot of the Department of Economics and Management "Marco Fanno"

The chatbot of the Department of Economics of the University of Padua started its activity on 16 April 2021. The idea of creating a chatbot was born during the Covid 19 pandemic to offer students a virtual assistant to support them in a period in which they can not interact in presence. The purpose was to provide a 24/24h assistant to current and future students capable of answering more common questions. The information it provides was already present on the website, but the chatbot allows one to find it quickly. The chatbot can immediately answer a question and give the link to the specific webpage if the user wants further details. In this way, the secretary should experience a workload reduction, consisting of fewer emails and calls to answer. Hence, the employees may save time in these repetitive activities and devote it to improving student services. In addition, the chatbot allows students to move quickly through the website pages. Indeed, the chatbot is not only an assistant for questions but also a quick search bar.

The Department adopted the platform Engati to implement the chatbot. The software provides an economical solution for the necessities of the Department compared to the other alternatives examined. Currently, the university staff placed the chatbot on the right-bottom of almost every page of the website Department (fig. 29). The user has to click on the red balloon with the dSEA logo to interact with the chatbot. First of all, the chatbot asks the user to choose a profile among bachelor's, master's degree, future student, other. If the user selects one of the first three options (bachelor's, master's degree, future student), the user must further identify himself. He has to choose his current course of study or that of his future interest. After this identification phase, the user can choose among the chatbot options (the predefined keywords displayed by the chatbot to search the topic of interest) or digit an open question in the specific blank. The chatbot invites the user to reformulate the open question if it does not understand the request or write an email to a tutor if it can not reply.

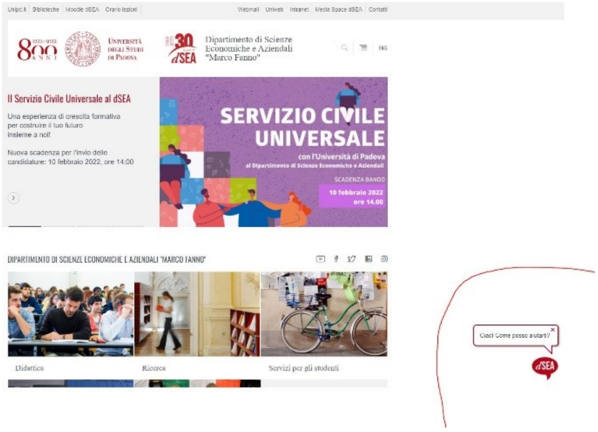


Figure 29: The chatbot is situated on the right-bottom of the Department of Economics website pages.

Currently, the chatbot provides information about the study plan, contacts, exams, classes, stage, thesis, study abroad. For future students, it informs about admission applications, course presentations.

The chatbot software adopts machine learning to learn from past interactions and improve itself. But currently, there are not enough interactions from which the chatbot can learn. Indeed, the software needs numerous past interactions to understand the users' behaviours.
According to Artificial Solutions (2021), the chatbot is a Hybrid Model as it combines both the rule-based and the machine learning model. The machine-learning algorithm allows the chatbot to answer open questions and improve interactions with experience. The rule-based model allows the user to choose among the suggested keywords to find the information of interest. It gives control over outputs and displays users what they can search in the chatbot.

According to Folstad et al. (2019), the Economics Department chatbot can be considered a chatbot for customer support. Indeed, it has a user-driven locus of control and short-term duration of relation. It is user-driven because the user interacts with the chatbot with a particular question or problem in mind. It has a short-term duration of relation because the chatbot does not collect data about the user to personalise future interactions. Therefore, a student should specify his course of study every time engages with the chatbot because it does not record the past users' information. The chatbot does not adopt push communication as it sends messages only after the user starts interacting with it.

3.4 Report on the chatbot activity between April and September 2021

This paragraph summarizes the chatbot's activity from 16 April to 17 September 2021. The data comes from the report provided by Francesco Ambrosini (2021), the assistant who handles the chatbot.

Number of users and interactions

Figure 30 shows new users vs active users. New users are the people who interact with the chatbot for the first time. Instead, active users have used the chatbot at least another time in the past. The Department published the chatbot the 16 April on a specific section of the website, but the peak of visits happened the 22 April, when the staff placed it on the homepage.

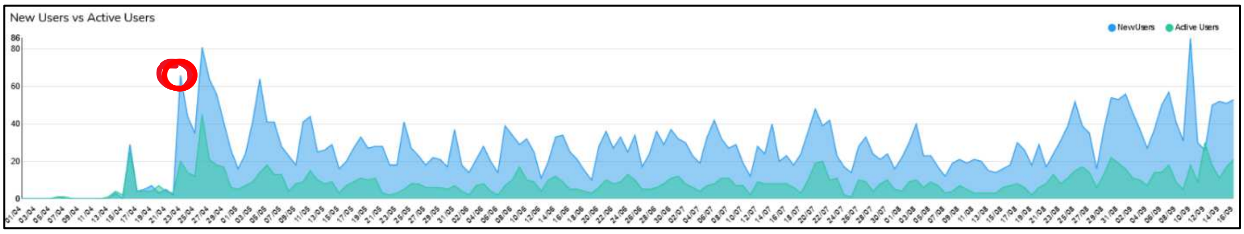


Figure 30: Frequency distribution of new and active users. The red circle indicates the peak of new users on 22 April when the staff placed the chatbot on the homepage. The first part of the graph is mainly composed of active users because it includes the interactions to testing the chatbot by the Department staff. Source: Francesco Ambrosini (2021).

Figure 31 shows that active users are more than total interactions. Hence, active users include those who click on the chat without conversating. Therefore, active users may be a dimension more relevant to understanding the use frequency of the chatbot because, compared to new users, it is more likely that a user clicking two or more times on the chatbot wants to ask a question.

Figure 31: Number of active users and total interactions. Source: Francesco Ambrosini (2021).

Figure 32 shows some metrics. Average interactions per user is the ratio of total interactions to new users. The average conversation duration is short: only 0.6 minutes (36 seconds). However, the metric may also include people who click on the chat without interacting but only out of curiosity. If it is the case, the duration could be double. The last metric - 6.2 - should consider the average number of replies the user gives to the chatbot. We should remember (par. 3.1) that the first two responses of the conversation are for identification. Again, the users who click on the chat without interacting, but only out of curiosity, may bias the result.

Figure 32: Some metrics about the chatbot activity. Source: Francesco Ambrosini (2021).

Conversations

Figure 33 shows the answers most clicked on the last 90 days before 17/09/2021. Data indicates that Bachelor's students are the main adopters of the chatbot, followed by Master Degree students, future students and others. It is reasonable as the Bachelor's students are more numerous than Master students. The proportions are coherent with the distribution of contacts received by tutors (figure 34).

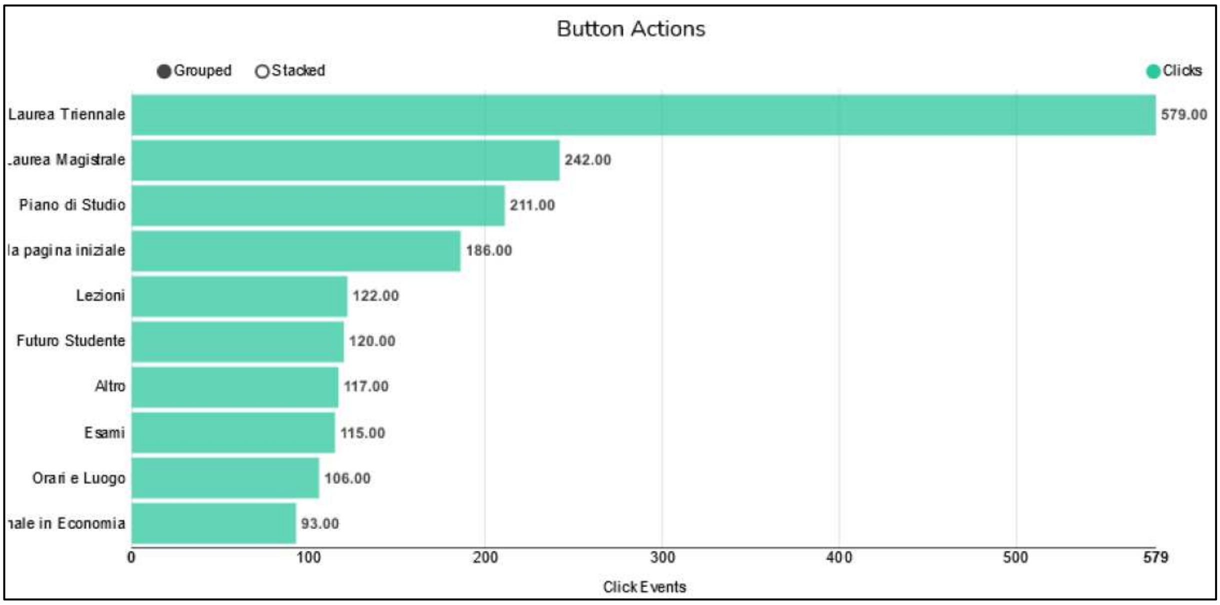


Figure 33: Number of clicks per answer on the last 90 days before 17/09/2021. Source: Francesco Ambrosini (2021).

Contatti per corso di laurea	N°	%
TrEC	53	38%
BA	18	13%
EI	10	7%
MED	3	2%
MEF	11	8%
ALTRO	45	32%
Totale	**140***	**100%**

Profilazione Chatbot	Clicks	%
Laurea Triennale	579	54,7%
Laurea Magistrale	242	22,9%
Futuro Studente	120	11,3%
Altro	117	11,1%
Totale	**1058**	**100,0%**

Figure 34: At the right, the distribution of students by course of study who click on the chatbot. On the left, there is the distribution of students by course of study who contacted the tutors. Source: Francesco Ambrosini (2021).

Figure 35 displays the distribution of the open questions asked through the chat. In blue, there are the answered questions - the questions to which the chatbot was able to provide an answer - while in green, there are the unanswered questions - the questions to which has not been able to give any response. The proportion of given and not given replies is 85% (figure 36). However, it has to consider that a provided answer may still not satisfy the user. The distribution of open questions (figure 35) can be considered the metric most representative of the chatbot adoption trend by users. Indeed, the users who click on the chat without interacting does not affect this metric as the distribution collects only those who was interested enough to ask a question.

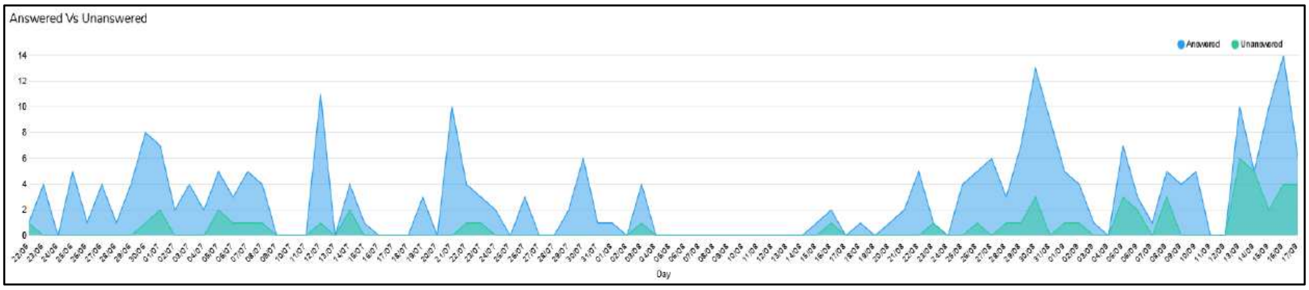


Figure 35: Distribution of the open questions asked through the chat. Source: Francesco Ambrosini (2021).

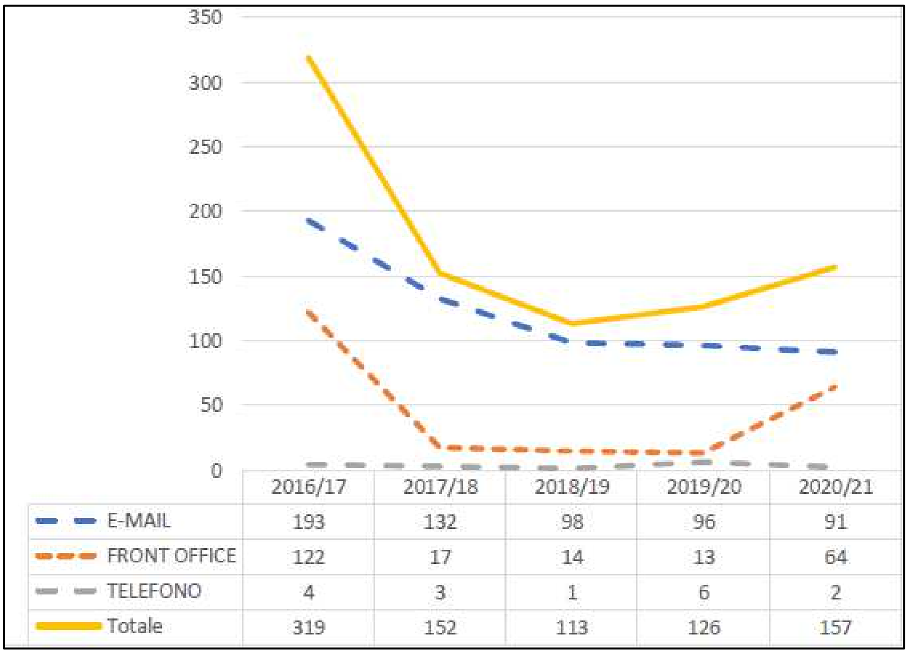
307	254	53
Total Questions Asked	Total Questions Answered	Total Questions Unanswered

Figure 36: Amounts of answered and unanswered questions. Source: Francesco Ambrosini (2021).

Utility of the chatbot

Research question RQ1.1 was: **Did the chatbot adoption help reduce the number of emails tutors received by students?**

As mentioned in paragraph 3.1, the number of contacts received by the tutoring service can be analysed to answer RQ1.1. The report of Ambrosini (2021) has already analysed the annual trend of the demands acquired by tutors from 2016 to 2021 (figure 37). Figure 37 highlights a continuing decline of emails over years.



	2016/17	2017/18	2018/19	2019/20	2020/21
E-MAIL	193	132	98	96	91
FRONT OFFICE	122	17	14	13	64
TELEFONO	4	3	1	6	2
Totale	319	152	113	126	157

Figure 37: Annual distribution of requests received by the tutoring service. Francesco Ambrosini (2021).

The chatbot adoption may have contributed to last year reduction. Indeed, a chatbot is suitable to answer most simple requests that are usually sent by email. Instead, more difficultly, the chatbot can substitute the front office or phone calls that are appropriate for more complex demands. Figures 38-39 show the monthly demand distribution of 2020-2021, and we can note a decline from April onwards when the staff implemented the chatbot. But the effect may be due to seasonality, as the university activity may be lower in those months.

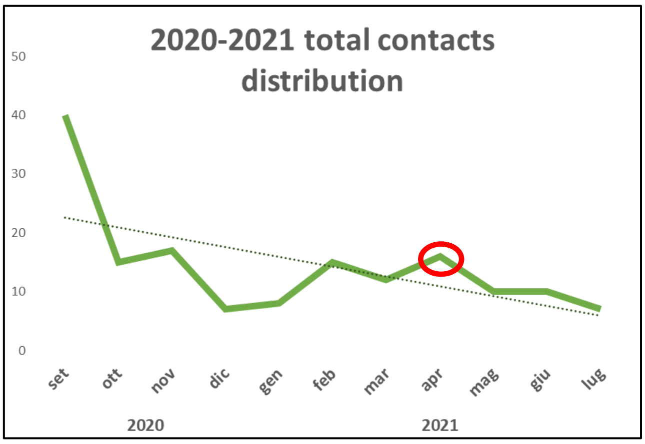


Figure 38

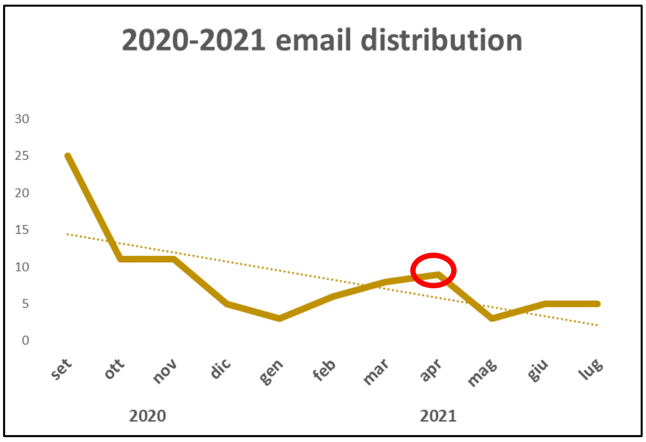


Figure 39

3.5 Comparison of the number of emails received before and after the chatbot implementation

We ended the previous paragraph by seeing a decline of contacts from April onwards when the staff installed the chatbot. But the effect may be due to seasonality as in that period the university activity may be lower than September-October when the University starts the year.

Therefore, now, the period 22/04-31/07 of 2021 was compared with the same interval of previous years to see if, in 2021, tutors received a lower number of emails because of the chatbot adoption (figure 40). This period was chosen because: on 22-04, the Department placed the chatbot on the homepage; the 31-07 was the last date covered by the tutor report of 2020-21. The period 16/04-21/04 was not considered because the staff mostly used it to do experiments instead of students. Figure 40 shows that excluding the academic year 2020-21, the other years have an increasing number of contacts from 22 April to May. However, the number of requests decreases from May onwards except for 2019-20. Thus, the drop in demands may be due to seasonality and not only to the chatbot implementation. The Covid 19 pandemic may explain the increase in requests of April-July of 2019-20 because of the confusion about the university continuation.

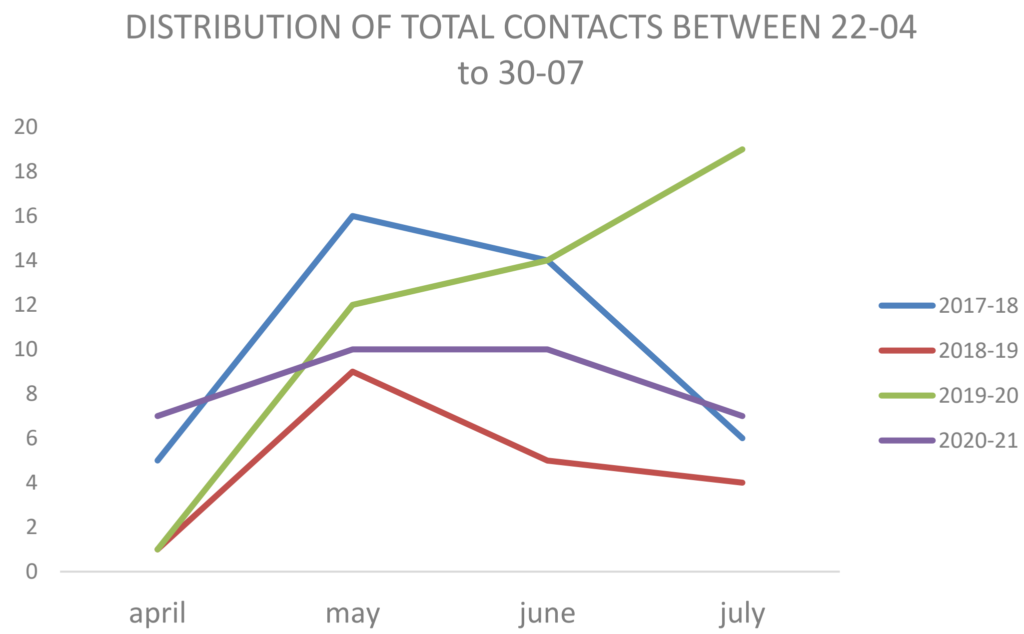


Figure 40

Figure 41 indicates the total number of contacts and the requests by email in those periods. We see that the lowest number of total requests happened in 2018-19, followed by 2020-21. The same for email requests (figure 42), with 2018-19 and 2020-21 years having about half of the emails received compared to the other years.

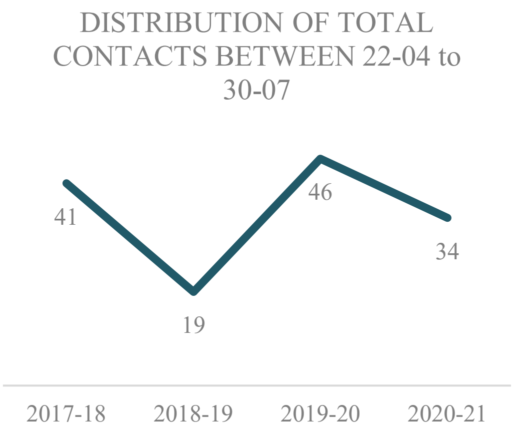


Figure 41

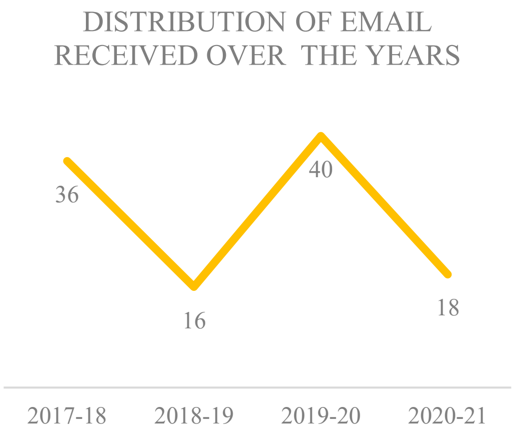


Figure 42

Conclusions

Was the chatbot effective to reduce the number of requests to tutors? We said that the number of emails is the parameter most reliable to estimate the chatbot efficacy because it is the mean of communication appropriate for not complex questions that could be answered by the chatbot.

From figure 37, we see that the distribution of emails over the years was declining, but the chatbot started its activity on the homepage on 22 April 2021. Therefore, the volume of emails received by tutors between 22-04 and 31/07 of 2021 was compared with the same period of 2017-18-19-20. The analysis indicates that in 2020-21 there were far fewer emails (18 emails) than in 2019-20 (40) and 2017-18 (36) but more than 2018-19 (16). However, it has to consider that the many emails received in 22-04 to 31-07 of 2019-20 may be due to the Covid pandemic. Indeed, the pandemic had just broken out and students may have sent many emails to ask for information about the continuation of the university. Therefore the high decrease of emails between 2019-20 to 2020-21 could also be due to the passing of the first phase of emergency of the Covid 19.

By counting the number of open questions asked by students to the chatbot in 22-04 to 31/07 2021 (figure 35), we note that: the chatbot answered 107 questions, and 12 of those remain unanswered. Hence, part of these answers may have satisfied a user that otherwise would have

contacted a tutor. However, there is no clear evidence of how much the chatbot may have contributed to reducing the number of emails received or only to help the user to find information faster. A future examination, with a broader period of investigation (1 year), could be helpful to get this point.
The conclusions over **RQ1.1 (Did the chatbot adoption help reduce the number of emails tutors received by students?)** are:

- The contribution of the chatbot to reduce student requests is unclear because tutors received fewer emails in 2018-19 when there was not the chatbot; the drop in emails from 2019-20 to 2020-21 could be due to the adjustment of the Covid situation.

- However, it is credible to assume some contribution of the chatbot since it answered 107 questions in that period.

3.6 Student survey

3.6.1 Methods

Objectives

This section analysed **RQ1.2 (What do students think about the chatbot of Economics? Do they appreciate the chatbot? What function do they like the chatbot could add?**).
RQ1.2 is composed of the following points:

- Analysis of the students' satisfaction with the chatbot of the Department of Economics of the University of Padua. The feedback was collected through a questionnaire.
- Understand students preferences for new future applications to adopt on the chatbot of Economics.

Modality of the study (Questionnaire survey)

I carried out the study through a questionnaire. Students may choose to complete the questionnaire between one of two modalities proposed: directly on Google Forms a) or through a Messenger link b) that randomly assigned him still on Google Forms or to a chatbot surveyor created to conduct the questionnaire. The two surveys modalities have the same questions, it changes only the conversation style adopted and the tool used to complete the questionnaire. The distinction was made only for the purpose of RQ2 that finds which survey method is the most effective. For RQ1.2 it was not relevant.
However, both the answers of the questionnaire collected through the two modalities were considered for answering RQ1.2., since the questions are the same.
Instead, only the questionnaire answers collected through the Messenger link were used. This is because the Messenger link distributed equally participants between the Google Forms survey and the chatbot survey. In this way, there are obtained two samples of participants of the same dimension and it is avoided the selection bias since the assignment to one of the two modalities is random.

If the participant chose the Messenger link b), the assignment procedure is:

First, the link opens a preliminary conversation on Messenger with the chatbot surveyor I have created.

Second, the user has to click on the "randomly assign" button, which with a 50% probability makes him stay on Messenger and start the questionnaire with the chatbot; otherwise, the button sends him to the Google Forms questionnaire (fig.43). Fig. 44 summarizes the selection process of participants to one of the two modalities.

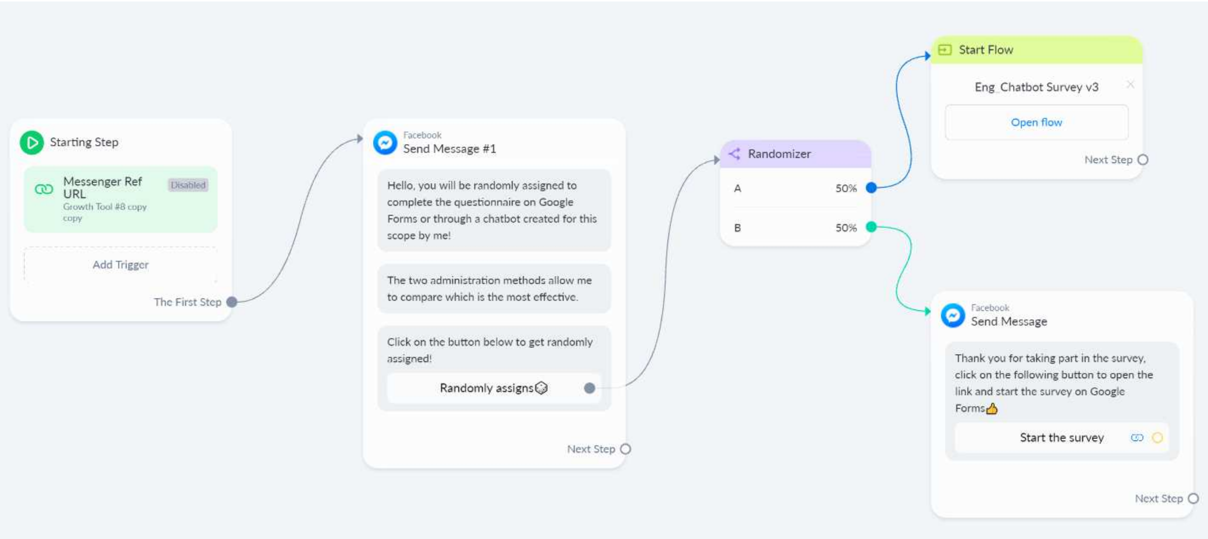


Figure 44: Process of selection if the participant uses the Messenger link (b). The user is randomly sorted to the Chatbot survey or the Google Forms survey after he clicks on the "randomly assigns" button.

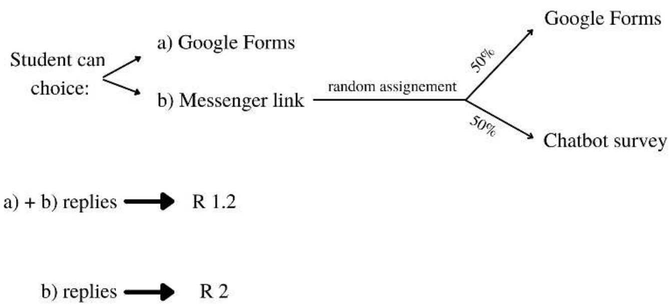


Figure 43: the process of the survey selection by the student.

The chatbot surveyor was implemented on Messenger, so anyone who wants to participate in this modality should own Messenger and a Facebook account. For this reason, a student that does not have Messenger could choose the Google Form option a).

Otherwise, the invitation suggested choosing the Messenger link to collect feedback about the two typologies of the survey and investigate which is better (RQ2, par. 3.7).

I developed the chatbot survey through Manychat, a software builder of automated conversation through Messenger, Instagram direct, SMS channels.

The survey was available in Italian or English for both modalities a) and b). The questions are the same, except the chatbot survey has a couple more evaluative queries on the satisfaction about the questionnaire filled. Moreover, a conversational interaction style was adopted in the chatbot survey, while a formal one in the web survey (Google Forms). It should lead to getting less satisficing responses, according to Kim et al. (2019). To have a conversational style, emoticons and more colloquial language were used while maintaining the equivalent meaning of the question (fig. 45). The chatbot can also call the participant by name to enhance the engagement in the conversation.

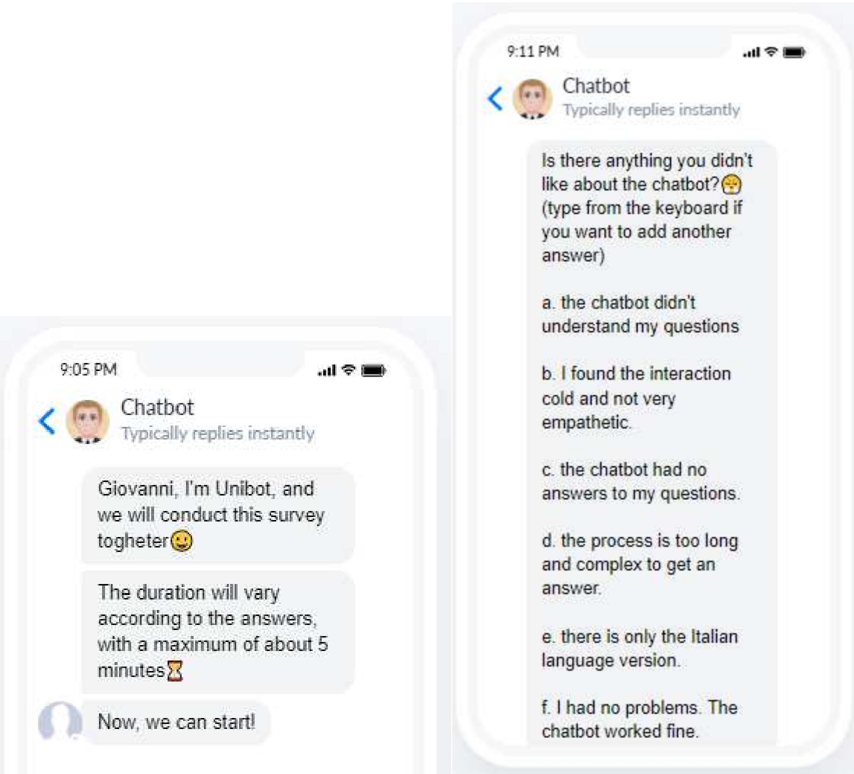


Figure 45: the chatbot adopts a colloquial language with the user.

The survey consists of multiple choices and Likert-scale questions.

The questionnaire is composed of four parts.

The first one regards the users' satisfaction with their experience with the Chatbot of Economics.

The second one regards gathering feedback about which future applications students would want the chatbot implements.

The third one is about collecting demographic data and characteristics of the participants.

The fourth part has some evaluative questions on the appreciation of the questionnaire completed. The answers expressed allowed us to understand which of the two modalities of questionnaire - Google Forms survey or chatbot survey - was the most appreciated. This last part will be discussed in par. 3.7.

The target of the questionnaire

I distributed the questionnaire to the students of the Department of Economics and Management "Marco Fanno".

Modality of distribution of the questionnaire

I asked the students to participate in the survey through three invitation modalities:

- With the cooperation of my supervisor, on 11-12-2021, I invited students of my supervisor's class to fill out the questionnaire before the lesson began. In this way, the adhesion was almost total by the students, and I collected 105 answers to the questionnaire. I distributed only the Google Forms type of questionnaire in that instance because it was the first experiment of the survey.
- On 29 December 2021, I asked students in the WhatsApp class groups where I was in to fill out the questionnaire.
- I asked the secretary of the Department to send an email to all the students of Economics in Padua, inviting them to participate in the questionnaire between 23 December and 6 January 2021-22.

I collected 213 responses in total. 105 out of 213 answers are from my supervisor class students of the first year of the Bachelor in Economics and completed the Google Forms questionnaire a).

The other 108 come from the invitation on the WhatsApp groups and emails.

78 out of 108 students chose the Google Form questionnaire a).

30 out of 108 students chose the Messenger link b) that assigned 15 of them the survey with the chatbot on Messenger; the others 15 were transferred to Google Forms. These 30 responses are analysed to answer RQ2 (par. 3.7).

The minority probably chose the Messenger link modality because some do not have Messenger, some believe the Google Forms of most simple use, some for privacy concerns nevertheless all the information collected were anonymized.

3.6.2 Results and discussion

This part reports and discusses the results of the survey. In the questionnaire, the questions were sequentially distributed in four sections: the participant satisfaction with the chatbot of Economics, feedback about future applications to implement on the chatbot of Economics, the participants' demographic data, the grade of appreciation of the survey completed.
To give first an overview of the participants' characteristics, I have anticipated the dissertation of the data gathered through the demographic questions.

Information about participants

The participants of the survey were equally distributed between males and females (figure 46). The prevalent age of participants is 19 years because I shared the questionnaire with my supervisor class of the first year of the Economics Bachelor (figure 47)

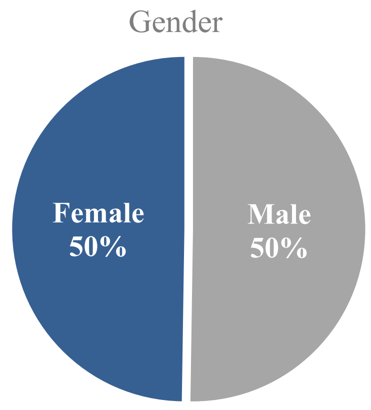


Figure 46: What is your gender?

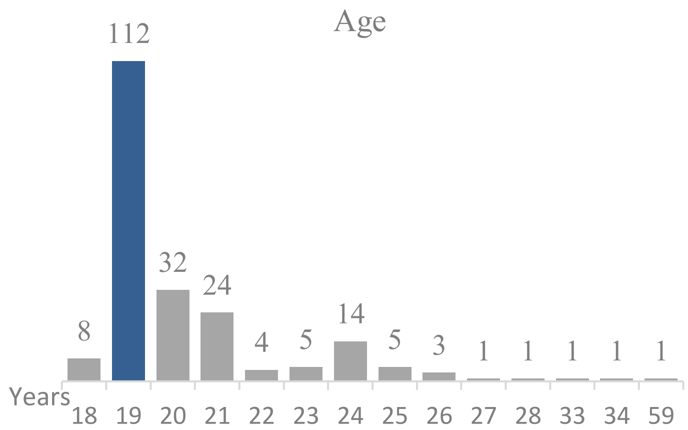


Figure 47: What is your age?

The students' majority knows what a chatbot is and has already interacted with it in the past (figure 48-49).

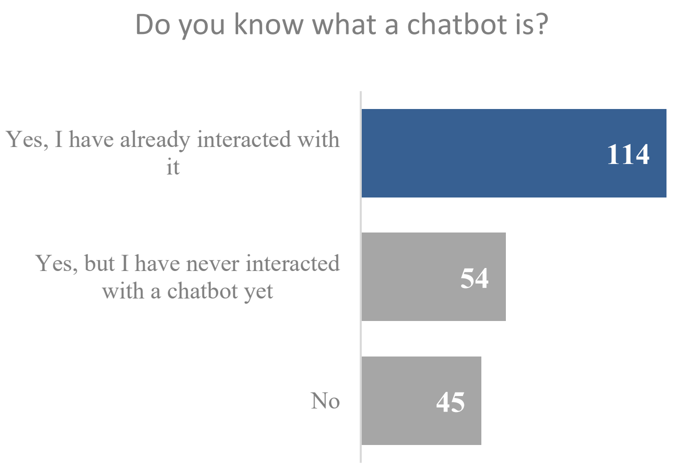


Figure 48: Do you know what a chatbot is?

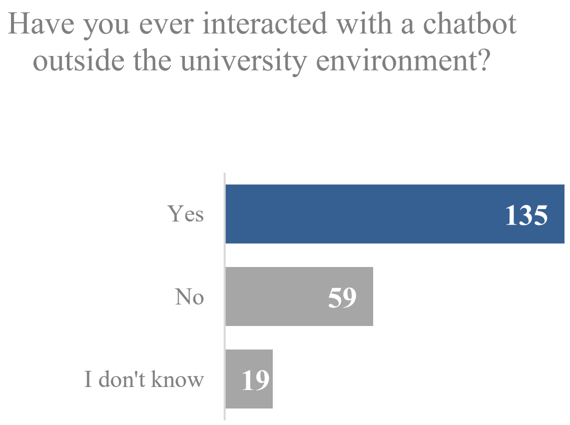


Figure 49: Have you ever interacted with a chatbot outside the university environment?

Most of the students come from a High Scholl, followed by Technical School (figure 50).

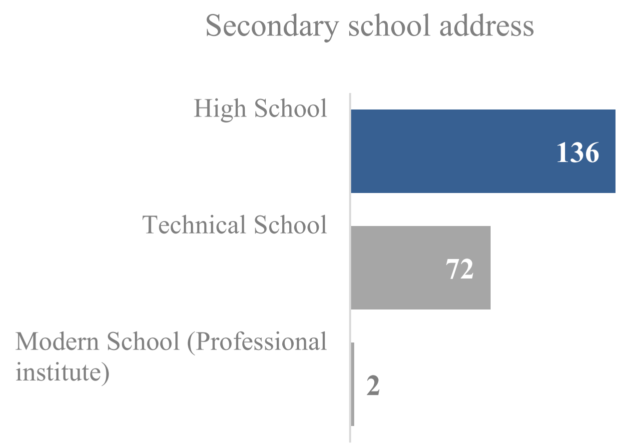


Figure 50:

The High School field most attended by students was the Scientific field, while the technical school students come mainly from the economic sector (figures 51-52).

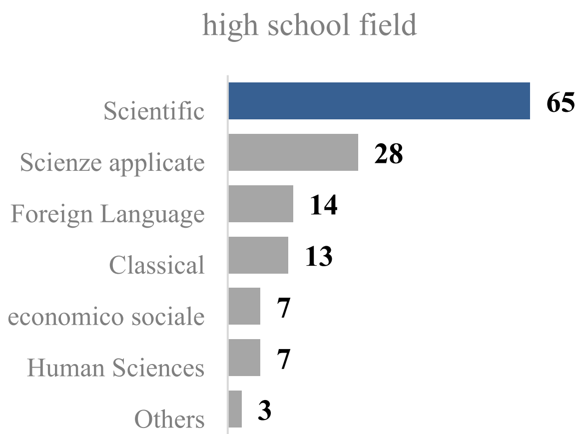


Figure 51: Which high school field did you attend?

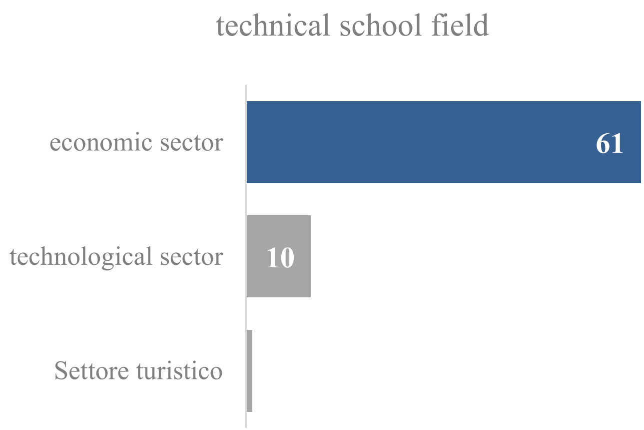


Figure 52: Which technical school field did you attend?

Most of the participants are attending the Bachelor in Economics (181 out of 213)(figure 53).

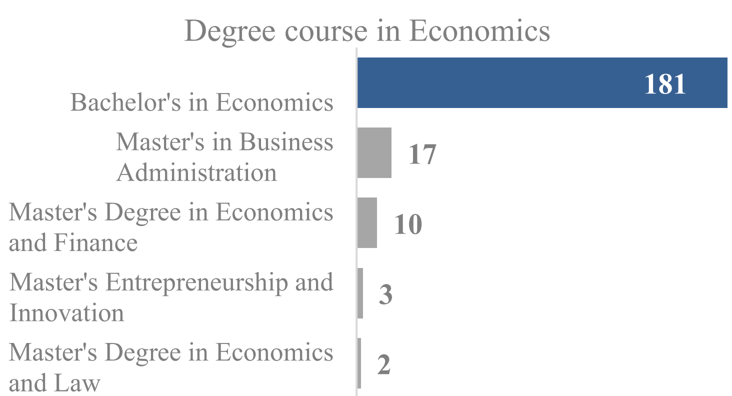


Figure 53

Most of the respondents are quite confident with new technologies. This question (figure 54) was asked to see if there is a correlation between the adoption of innovations and the use of the Economics chatbot. This is not the case as figure 55 shows.

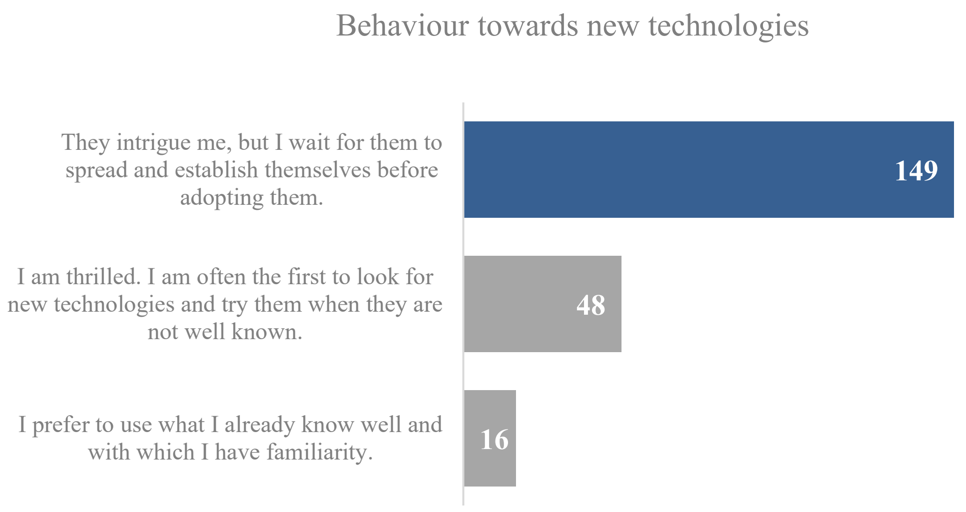


Figure 54: How do you usually behave towards new technologies?

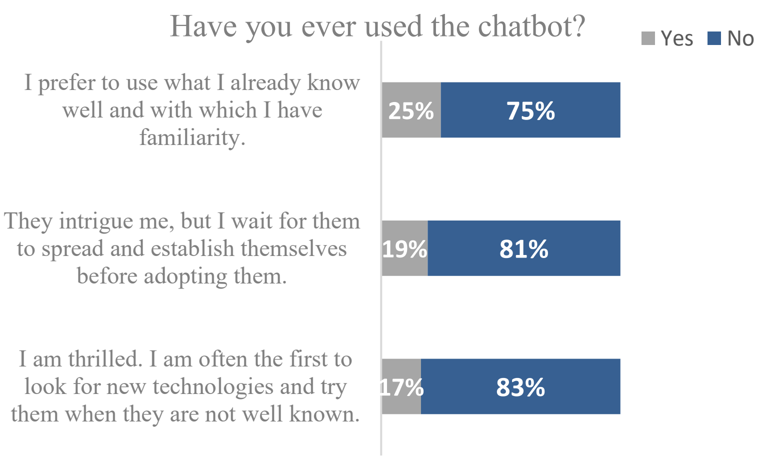


Figure 55: the chart shows no correlation between technology adopters and the use of the chatbot.

A large part of the participants opens only the university emails that appear more interesting, while a slightly smaller number reads almost all the emails received; finally, some students rarely open emails (figure 56). In addition, about half of the respondents answered that they have missed reading an important email from the University (figure 57).

This data allows understanding the effectiveness of the email channel to share information. The results suggest that emails may not always effectively reach students as they are uninvolving and without personalization. Chatbots can overcome these problems since they are more engaging and chatbot push notifications (SMS, Messenger messages) may have more visibility than emails. Therefore, the staff of Economics may consider adopting the chatbot Broadcast channel to send messages to students.

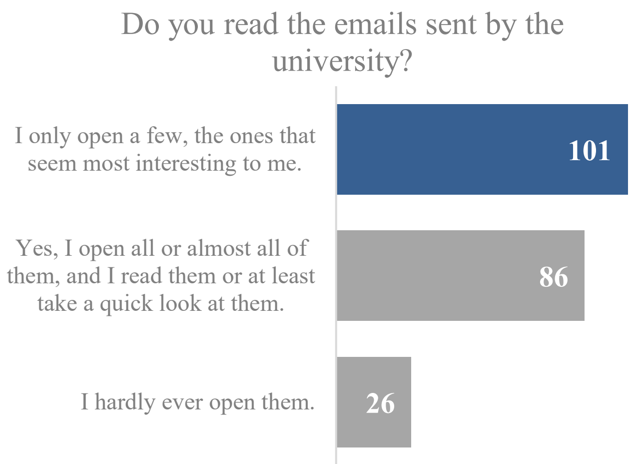


Figure 56

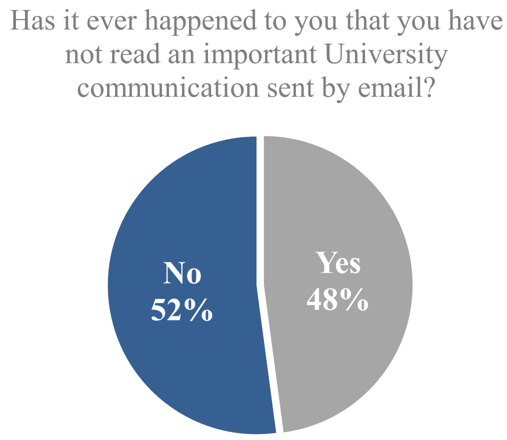


Figure 57

The participant satisfaction with the chatbot of Economics

About 20% of participants have already used the chatbot of Economics (figure 58). The data could be different from the proportion of the entire population of students because those who have already interacted with the chatbot may be more inclined to participate in the questionnaire. 45% of participants prefer to use other means than the chatbot to find information, while nearly 30% of those who did not use the chatbot did not know its existence (figure 59).

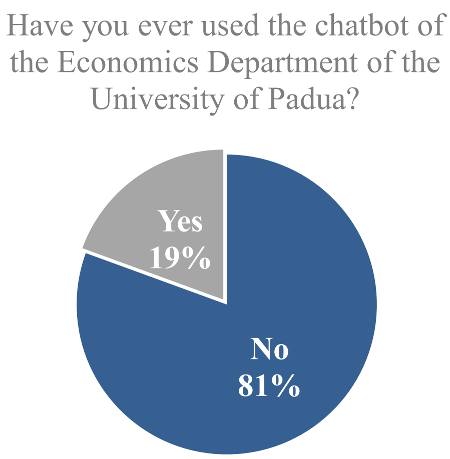


Figure 58

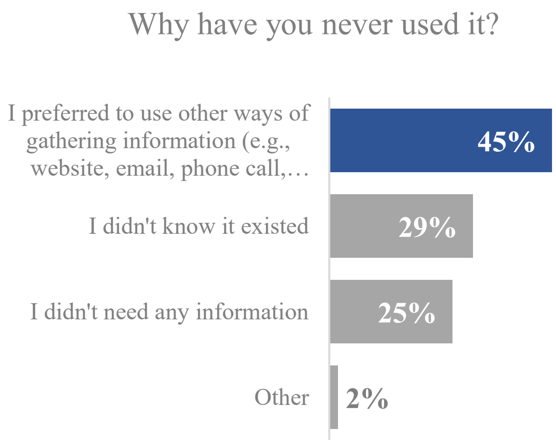


Figure 59

Participants who interacted with the chatbot expressed a good level of satisfaction (average rating: 3.41) (figure 60). The most appreciated factors of the chatbot were that it allows to search for information and quickly navigate through the website(figure 61).

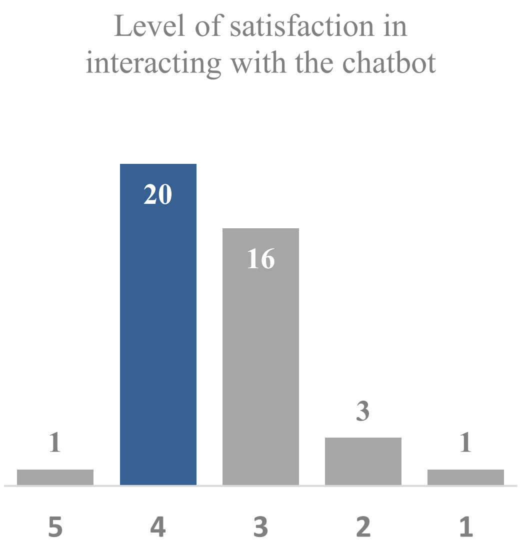


Figure 60

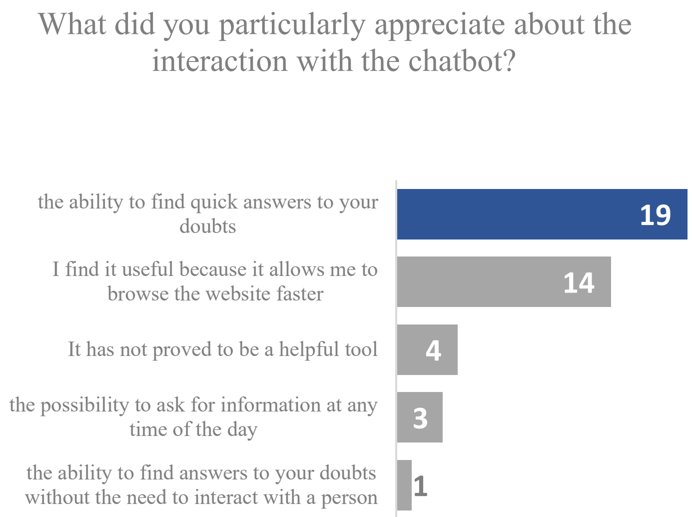


Figure 61

Most of the participants do not find problems with the chatbot (fig. 62).

Whose reports problems with the chatbot was because it could not understand and reply to questions effectively.

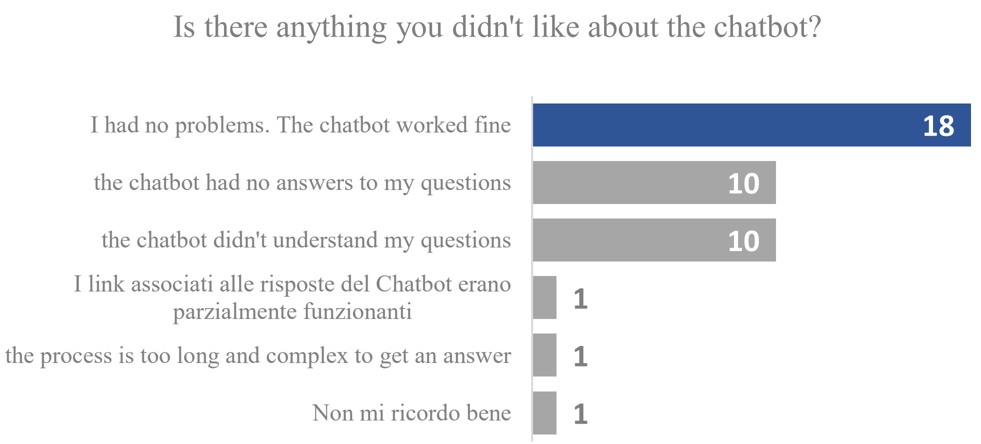


Figure 62

The information most searched were about the study plan and the exams (figure 63).

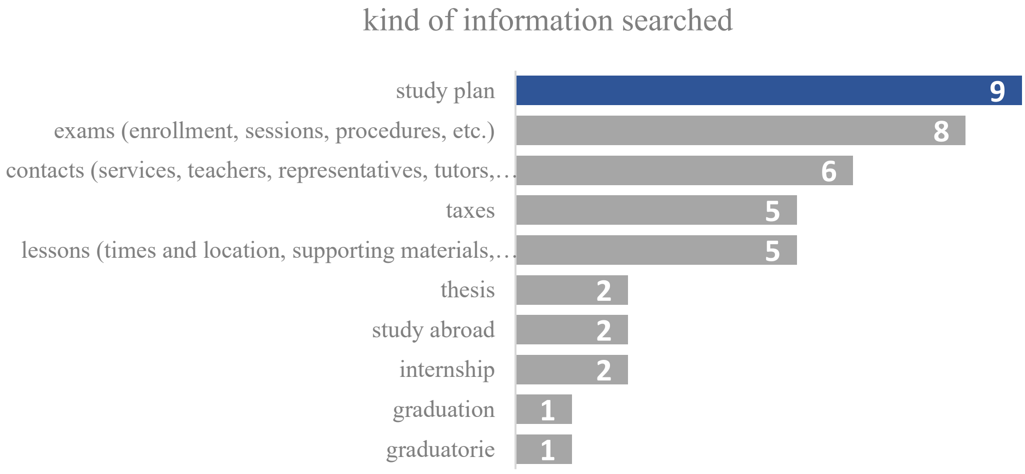


Figure 63

Most of the participants who have used the chatbot find at least partially an answer to their doubts (figure 64). However, about half of them (46%) had to recur to another means of communication to find information after the chatbot interaction (figure 65).

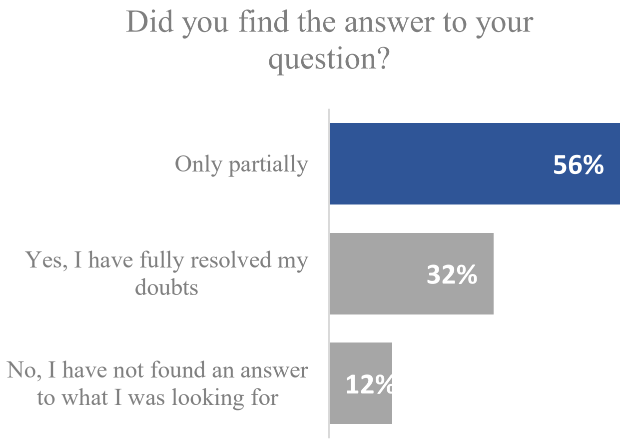


Figure 64

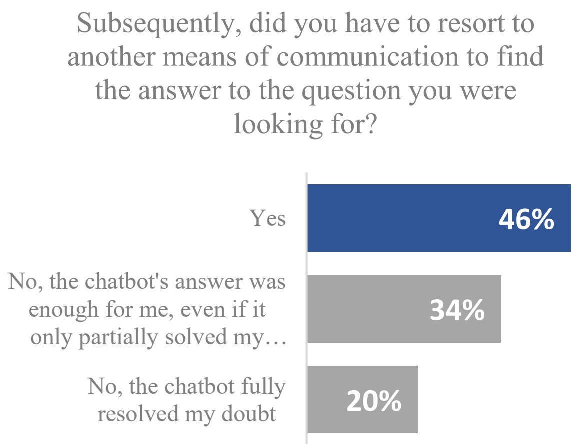


Figure 65

Feedback about future applications to implement on the chatbot

In this part, students express their preferences about possible future functionalities of the chatbot. Most of the questions asked to give a grade between 1 to 5 to the proposal.

80% of participants were favourable that the chatbot could access the Uniweb data of students to personalize the interaction experience (figure 66). In this way, a student that has done the

Uniweb access can skip the first two identification questions of the chatbot about the course attended. Moreover, the chatbot can use Uniweb data to send personalized messages according to the user. About this, many respondents would agree to receive push notifications that remind them of expirations like the sending of the university fees and the sending of the application for benefits (average rating: 4.45) (figure 67).

Most would also agree to interact with the chatbot outside of the website through Messenger or SMS channels (figure 68). Therefore, the Department may consider sending personalized messages to its students. For this purpose, the broadcast function of the chatbot could be an option. However, students should maintain the possibility to change the notification settings according to their preferences to regulate the type and the frequency of messages they receive.

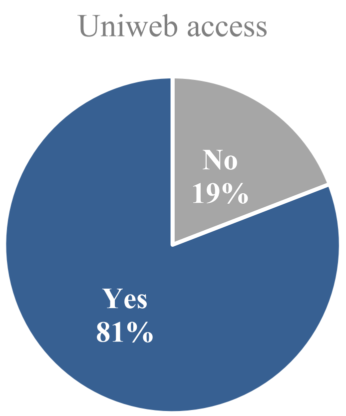


Figure 66

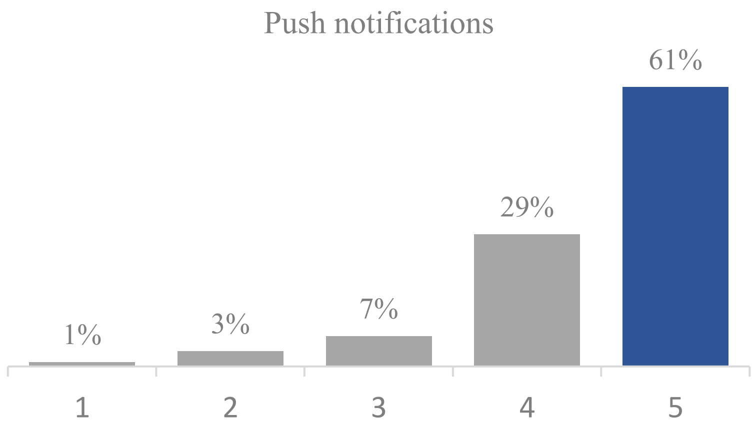


Figure 67

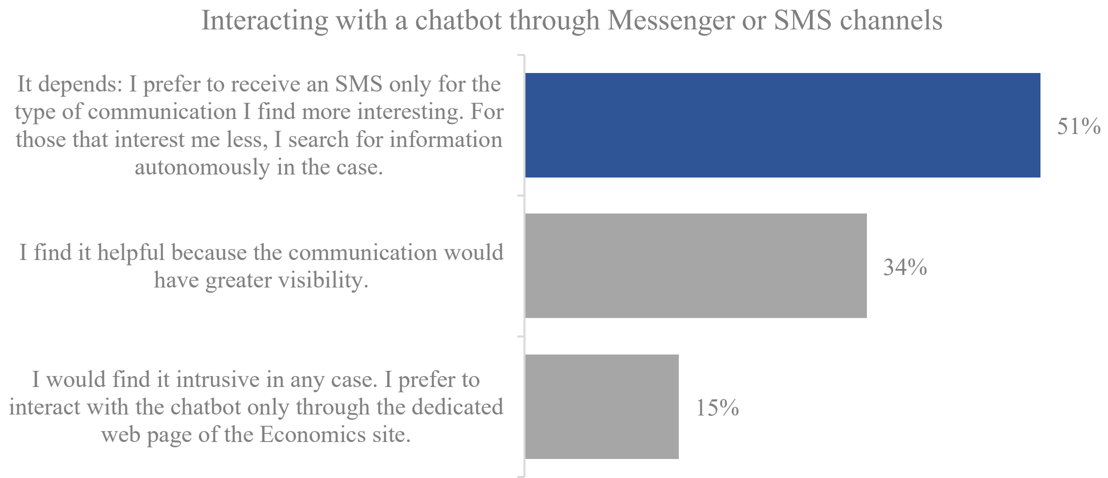


Figure 68

Most participants would appreciate the chatbot provides orientation suggestions (average rating: 4.28) (figure 69).

They also appreciate that the chatbot communicates jobs and internship offers consistent with their study plan (average rating: 3.89) (figure 70).

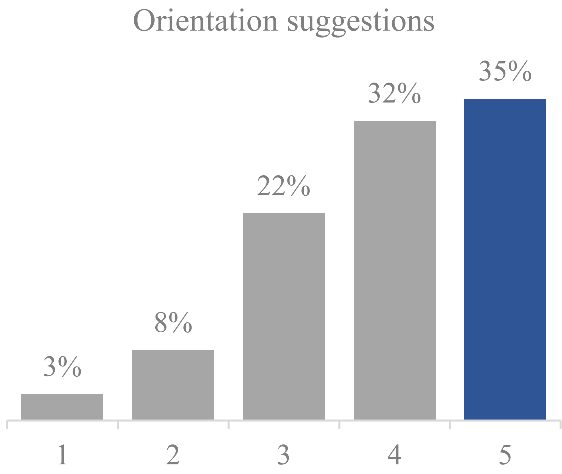


Figure 69: Orientation suggestions (e.g., the choice of the field of study, study plan, optional courses) based on the preferences expressed to the chatbot through some aptitude questions. The chatbot would also consider the typology of the attended courses - unless the student is a freshman- and the grade got in them as an aptitude estimate.

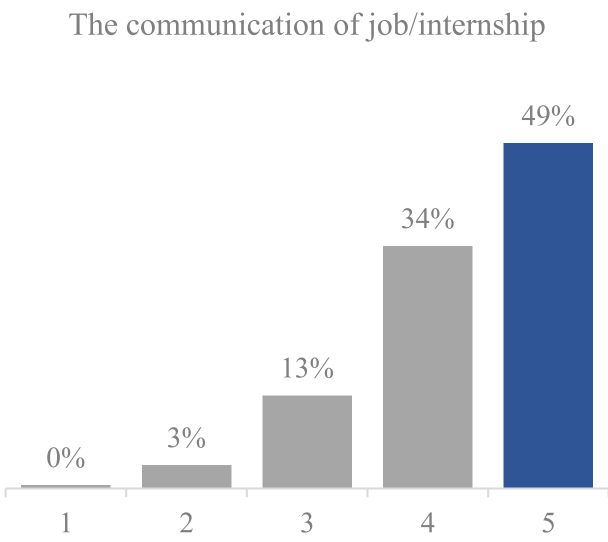


Figure 70

The degree of satisfaction of the interviewees is more varied as regards the possibility that the chatbot sends communications of events and opportunities such as seminars, webinars, student projects, career days (figure 71). Also, the possibility to send periodic anonymous feedback on the quality of study courses and university services does not collect a clear consensus (most gives 3 out of 5)(figure 72).

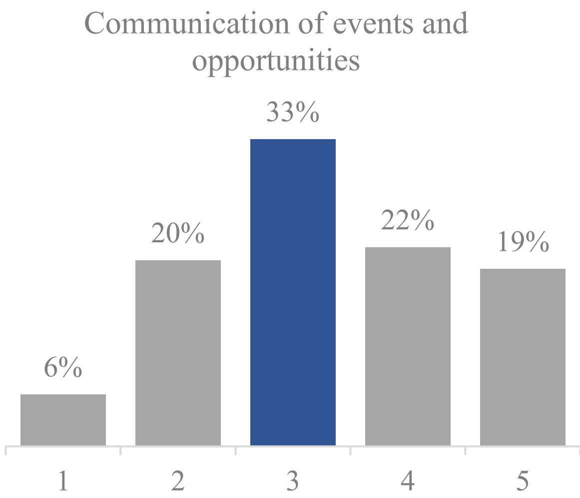


Figure 71

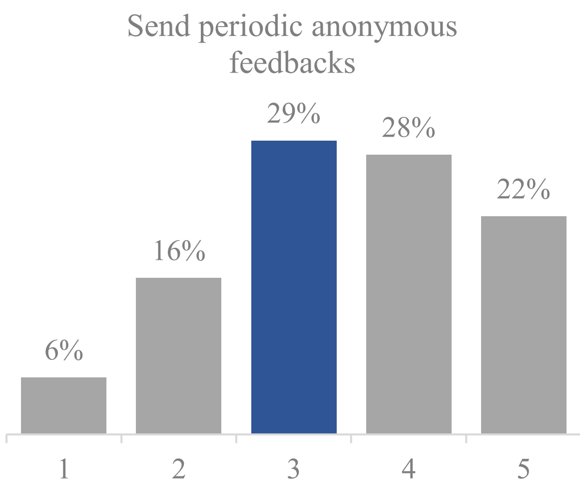


Figure 72

3.6.3 Findings of the survey

Research question **R 1.2** asks: **What do students think about the chatbot of Economics? Do they appreciate the chatbot? What function do they like the chatbot could add?**

The survey highlights a general appreciation of students for the chatbot of Economics (average rating of 3.41/5)(figure 1). Students appreciate that chatbot allows having quick answers to their doubts. They also like that chatbot allows surfing quickly on the website. The problems most cited by the participants were that the chatbot could not understand the questions correctly or could not answer the questions (20 out of 41 respondents). Hence, the problem refers to when the user asks open questions to the chatbot, and the virtual assistant does not understand or gives an incorrect answer. However, the chatbot is equipped with machine learning which should improve understanding through the accumulation of experience over time. Additionally, staff should add new content to the chatbot that users have often searched for and are not already there. Therefore, this problem should decrease with time.

Generally, for now, the chatbot can not fully answer users doubts. Indeed, more than one-half of participants have only partially found answers to their questions, and about one-half has to resort to another means of communication to be satisfied. Presumably, the chatbot can answer only the most simple questions of users.

As for the new chatbot applications, participants would appreciate push notifications that remind them of deadlines like the university fee payment and the application for benefits (rating: 4.45/5). Accordingly, they agree to receive chatbot communications relevant for them through the Messenger or SMS channel. They also like receiving communication of job/internship offers in line with their study plan (rating: 4.28/5). They appreciate too that the chatbot could give orientation suggestions (e.g., the choice of the field of study, study plan, optional courses) based on the preferences expressed to the chatbot through some aptitude questions (rating: 3.89/5). The chatbot would also consider the typology of the attended courses -unless the student is a freshman- and the grade got in them as an aptitude estimate.

3.7. Benefits and cost analysis of the chatbot implementation

This paragraph answers **RQ1.3: What is the economic impact of the chatbot on the Department of Economics?** I considered the costs, the savings and the potential revenues the chatbot could generate to investigate whether the outcome is positive. I assumed three years of projections and computed the present value at time 0 (year 2021), the year when the Department set up the chatbot. I considered an early discount factor of 10%.
We see first the list of costs and then the savings and revenues related to the chatbot.

Costs

I start viewing the costs. The expenses are: the annual fixed fee to pay to Engati, the platform that distributes the software; the payment of the staff that manage the chatbot.

Fee subscription

- Currently, the Department pays the Engati professional plan that yearly amounts to 869\$=775€ (869\$/1.121).

Staff costs

The main staff costs for the chatbot management are:
- Paying the assistant who provides chatbot data reports and applies adjustments to the chatbot settings. His contract is for 100 hours at a 20€ hourly cost.
- The time tutors are currently spending to translate the chatbot content. Tutors are paid 16€ hourly and it is forecasted they spend 30 hours on the chatbot.

Costs						
year	initial-2021		2022		2023	
annual fee		**€ 775**		**€ 775**		**€ 775**
assistant hourly cost	20		20		20	
assistant total hours	100		100		100	
total assistant cost		**€ 2.000**		**€ 2.000**		**€ 2.000**
tutor hourly cost	16		16		16	
hours dedicated by tutors	30		20		15	
total tutors cost		**€ 480**		**€ 320**		**€ 240**
total costs		**€ 3.255**		**€ 3.095**		**€ 3.015**

Figure 23: costs related to the chatbot adoption.

Savings and revenues

Now, we see the savings and revenues the chatbot provide. The values reported are estimations of the savings and revenues because it is difficult to quantify the link between the chatbot activity and the economic benefit.

Conversation Containment Savings

The chatbot should reduce the number of emails and calls the secretariat and the tutoring service receive.
The chatbot collected 965 interactions in its first semester of activity (16 April to 17 September) (figure). Hence, I estimated an annual number of interactions of 1930 (965x2). I consider that 46% of the survey participants resorted to another means of communication to find the answer to the question they were looking for (email, telephone call, face-to-face interview, etc.). Hence, the effective success rate was 54% (100%-46%). However, 46% may include users that when they are not satisfied with the chatbot search on the website or ask friends, instead of contacting the secretariat. Indeed, likely, many students use the chatbot to quickly search for the information they usually find on the website and not as an alternative to contacting the secretariat. Therefore, only 50% out of the 54% were considered to use the chatbot as an alternative to email or call the secretariat/tutors. Finally, the chatbot would save 54%x50%x1930=521 emails/calls over the first year of the chatbot adoption. I assumed an average time to solve the problem of the email/call of 5 minutes. I considered an hourly job cost (the hour cost of a tutor) of 16€. Hence, every email/call saved is 1.33€ (16€x5/60).
Interactions were estimated to increase by 15% in 2022 and 10% in 2023.
The effective rate is assumed to improve over time because of the chatbot developments: Y1=54%; Y2=60%; Y3=65%. It was considered an adjustment for risk of 10%.

Savings					
year	initial-2021		2022		2023
n° of interations in six months	**965**				
annual increase in interactions		15%		10%	
forecasted interactions in the year	**1930**		**2220**		**2441**
effective rate of 54%	54%		60%		65%
	1042		**1332**		**1587**
50% users use the chatbot instead to email/call	50%		50%		50%
	521		**666**		**793**
hour cost of work	16 €		16 €		16 €
average time to solve the interaction by email/call (minutes)	5		5		5
cost for email/call	1,33 €		1,33 €		1,33 €
risk adjustament	10%		10%		10%
savings	**625 €**		**799 €**		**952 €**

Figure 74: savings achieved through the chatbot adoption.

Revenues

The chatbot could increase the enrolment rate of new students to the Department of Economics. A case study of a University that adopted a chatbot was Winston-Salem State University (WSSU) in 2017. The University noted that email and phone communication were not engaging enough to help new students prepare for the college experience and so decide to install a chatbot (Mainstay, 2020). One of the main purposes of the chatbot was to assist students in completing enrolment steps about immunization compliance and bill payment. The university recorded a 2% increase in enrolment. The WSSU chatbot was part also of a broader activity of engagement with its students but it is reasonable even the chatbot of the "Marco Fanno" Department could increase a bit its enrolment rate. Indeed, the chatbot can provide information on the enrolment appliance to potential new students and assist them.

Therefore, while remaining conservative, I estimated there was no increase in subscriptions in the year the chatbot was installed (2021). Then the enrolment rate increase is forecasted to be 0.5% and 1% in 2022 and 2023. The number of newly enrolled students is calculated as the increase in matriculated rate times the number of new students enrolled. I considered the last data available, in 2019, of the number of students enrolled in Economics (373, source: https://www.unipd.it/dati-statistici-immatricolati). The number refers only to students enrolled on the Bachelor in Economics. Moreover, nowadays, the number is presumably higher. Therefore I assumed 450 enrolled students in year 0 and I maintained the number constant, thus increasing it only for the part attributable to the chatbot (enrolled in 2022= 450x(1+0.5%)).

I estimated the profit per student by dividing the total teaching income of the University of Padua by its number of students (source: https://www.unipd.it/trasparenza/bilancio-preventivo-consuntivo). I assumed that the increase in the number of students should not impact costs.

To take into account this aspect and other possible errors in estimation, I applied a risk-adjusted factor of 10%.

Incremental profits				
year	2020	initial-2021	2022	2023
students enrolled	450	450	452	457
enrrolment increase		0%	0,5%	1,0%
enrollment increase: increase in n° of students		0	2	5
profit per student		€ 1.635	€ 1.652	€ 1.665
risk adjustement		10%	10%	10%
total incremental profits		**€ -**	**€ 2.974**	**€ 7.492**

Figure 75: profits generated by the chatbot adoption.

Unquantified benefits

The chatbot also presents other benefits that are difficult to quantify:

- Fewer repetitive tasks for the secretariat staff and the tutoring service. The chatbot should reduce the number of emails received for the more common and simple questions that the chatbot can respond to autonomously. Therefore, the staff should be alleviated from a boring part of the work and can focus on more engaging tasks.
- The chatbot can handle large volumes without hiring additional employees.

Chatbot economic impact

Figures 76-77 shows the free cash flow table and chart related to chatbot adoption.

The conclusions over research question **RQ1.3** are:

- The chatbot investment has a positive economic impact with an ROI of 29% (PV of net benefits/ PV of total costs). In the initial year of the chatbot installation, total costs exceed benefits, while from 2022 it is expected benefits to surpass the costs of the year. In the year 2023, it is expected a complete return from the investment. Moreover, the benefits of the chatbot are expected to increase over time as the staff improve its content and functionalities.

Cash flow table				
year	initial-2021	2022	2023	present value
savings	625 €	799 €	952 €	
profits by enrollment increase	€ 0	€ 2.974	€ 7.492	
total benefits	625 €	3.773 €	8.444 €	**11.034 €**
total costs	-€ 3.255	-€ 3.095	-€ 3.015	**-€ 8.560**
Net benefits	**-€ 2.630**	**678 €**	**5.429 €**	**2.473 €**
Cumulative net benefit	-€ 2.630	-€ 1.952	6.107 €	
ROI				**29%**
Payback period				**3 years**

Figure 76: estimated economic impact of the chatbot adoption.

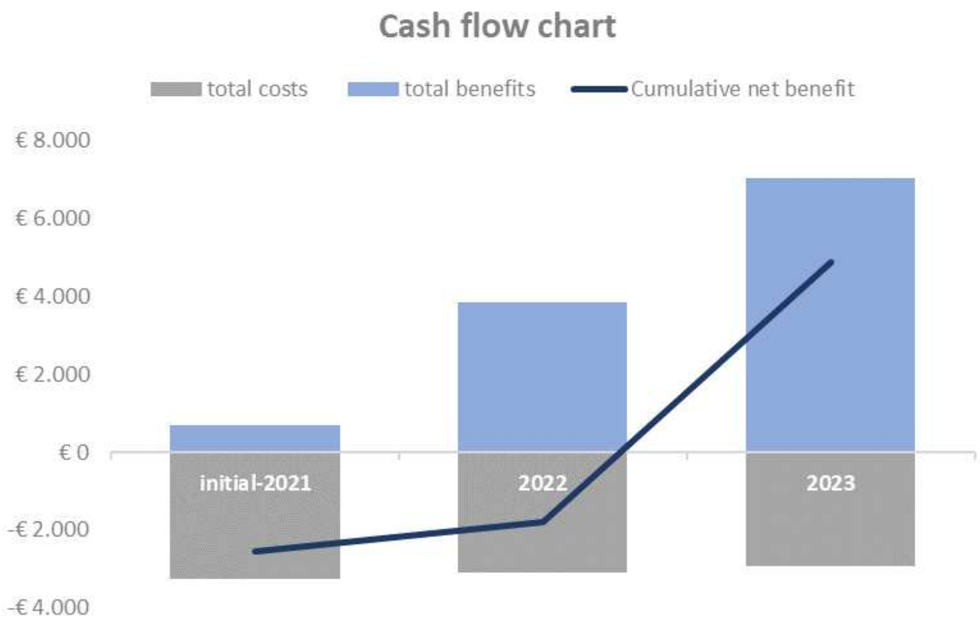


Figure 77: the chatbot adoption expects to have a positive cumulative net benefit in 2023.

3.8 Chatbot survey vs Web survey

This section investigated **RQ2: Could a chatbot survey be more effective than the classical questionnaire distributed with Google Forms?**

I compared the effectiveness of a survey conducted through Google Forms (web survey) and a chatbot. Indeed, I have surveyed for this study, and I have distributed the questionnaire in both these two modalities. In particular, I compare the thesis results with the findings of Kim et al. (2019).

The research of Kim et al. (2019) conducted a 2x2 experiment by comparing the web survey with a formal or casual style of interaction with a chatbot survey adopting the same two interaction styles. They find that the participants of the chatbot survey were more likely to produce differentiated responses and less likely to satisfice than those in the web survey. "Satisficing is a decision-making strategy that aims for a satisfactory or adequate result rather than the optimal solution" (Frankenfield, 2021). In a survey, satisficing means that respondents do not put much effort into answering questions, leading to results not being so reliable. Participants may adopt satisficing behaviours because they may be lazy and want to finish the questionnaire quickly and without too much effort.

Also, the survey design may affect the quality of answers. For example, the respondents may get bored and give inaccurate replies when the questionnaire is too long or repetitive.
They also find that the chatbot adopting a casual tone makes users less likely to engage in satisfying behaviour. The same does not happen for a web survey with an informal interaction style.
The explanation could be that the questionnaire effectiveness requires affinity between the platform and the conversational style. Indeed, a web survey is not well suited for a casual tone, while a chatbot can effectively adopt it as it resembles a human conversation. The difference in interactivity between chatbots and web surveys can explain the diversity in satisficing. Web surveys adopt a table matrix interface, grouping similar questions in a grid form that can lead to a loss of attention and engagement by some users. Instead, respondents perceive chatbot as a conversational interface that allows interpersonal interactions similar to those of two people. In this way, questions are not perceived as a task to complete. Chatbots partially assimilate the

offline survey of a human interviewer who, with his presence, promotes participation and focus in replies. Differently, web surveys elicit satisficing responses since they are self-administrated.

Kim et al. (2019) conducted their experiment on 117 adolescents of Korea through a questionnaire on Internet usage behaviour.
I repropose the experiment of Kim et al. (2019) to the students of Economics of Padua to compare their results with my research.

Therefore, I compared a web survey (Google Forms) with a chatbot survey that adopts a conversational interaction style. As I described in the method paragraph (par. 3.6.1), the conversational style was obtained by the adoption of a casual tone and the use of some emoticons, while maintaining the same meaning of the questions. Moreover, the chatbot can call participants by their names to reinforce the engagement in the interaction. With survey questions incorporated into dialogue, participants might perceive the survey as a conversational exchange of questions and answers, rather than as a task to be completed (Kim et al., 2019).
The improvements compared to a web survey are more satisfied participants and less satisficing responses. To compare the two surveys methodology, two points were evaluated:

- Satisfaction of respondents: which of the two surveys did the participants find more engaging, easy to use and pleasant?

- Does the chatbot survey reduce satisficing answers? Satisficing verifies when survey respondents give not optimal replies to lower the cognitive work necessary to fill out the questionnaire. According to Kim et al. (2019), a chatbot survey should induce more accurate participant answers because it recreates an interpersonal interaction that stimulates his attention as if the respondent was in front of a human interviewer. In particular, this happens when the chatbot adopts a conversational interaction style resembling that of a human colloquial. Therefore, respondents should answer with more variety to questions. To verify this, I consider the Likert questions and calculate the index of response differentiation of the answers. The answer differentiation of the chatbot survey replies should be higher than those of the web survey on Google Forms. This is because the participant of a chatbot survey is more likely to produce differentiated responses and less likely to satisfice.

I considered only questionnaire answers to the Messenger link b) for this part. In this way, I had two samples of participants comparable. The Messenger link collected 15 answers from the Google Form survey and 15 from the chatbot survey.

Participant satisfaction of the survey

I got the following results by the expression by Participants to a grade from 1 to 5 to some Likert questions. These questions were asked both to respondents of the Google Forms and chatbot survey. Then I compared the results.

Most of the participants appreciate more the chatbot survey than the Google Forms survey (figure 78).
Also, they find the chatbot modality more pleasant to complete (figure 79).
These results can be explained because the Chabot engaged the user in a more personalized experience. Indeed, it interacted with a conversational style, while the web survey was formal and more boring. Then, the chatbot can call the participant for his Messenger name since he logged in through it. Furthermore, the chatbot recreates the timing of an interpersonal dialogue as each chatbot question followed the previous user answer. This is because the chat interface may heighten the sense of back-and-forth messages in the mind, thus driving user engagement (Kim et al., 2019). These aspects contributed to creating a deeper conversation with the user.

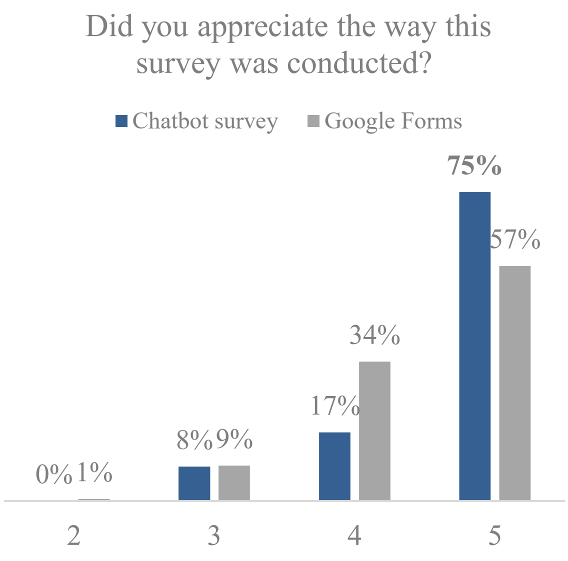


Figure 78

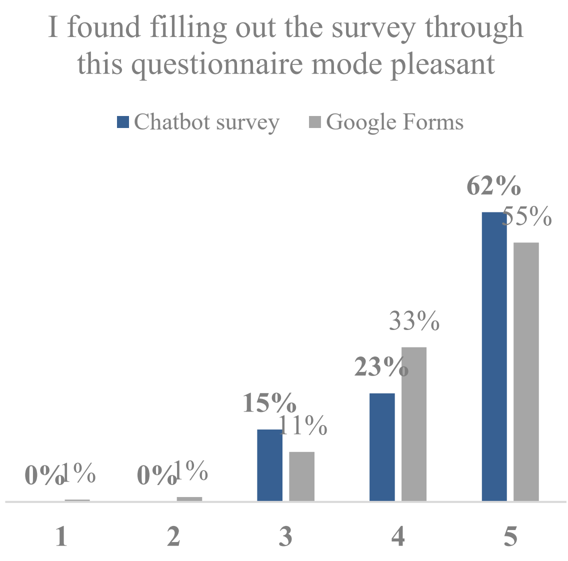


Figure 79

On the other hand, the modality to participate through the Messenger link (modality b) may have dissuaded someone to join in and this could explain the less adoption of this modality (30 respondents used the Messenger link b), the other 78 participate directly through Google Forms a). One reason could be that it is an innovative way to conduct a questionnaire that may have discouraged those who want a traditional way to participate. Moreover, the fact that the chatbot has access to public data on Messenger as the name, may disturb the privacy of someone.
Otherwise, more simply, many of the participants did not have Messenger and thus chose the Google Forms modality a).

Participants find the chatbot survey slightly more complex to use than the Google Forms one (figure 80). It is reasonable because the interface of Google Forms may appear more intuitive and easily allows to change a previous answer.

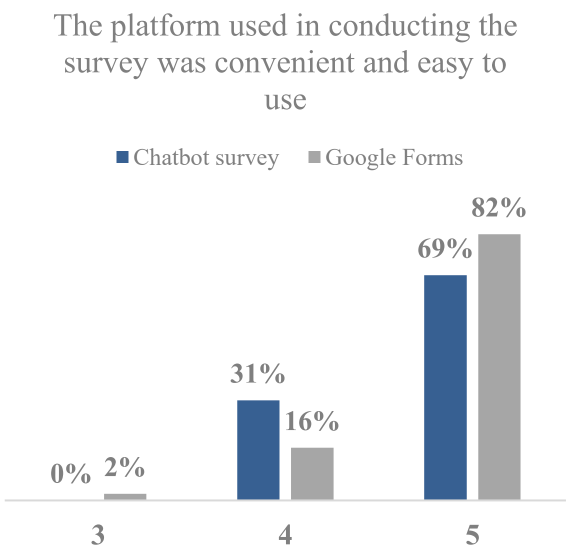


Figure 80

The chatbot survey asks some more questions than the Google Forms questionnaire. First of all, it asks whether the respondent has ever responded to a web survey in the past.
If so, it asks the respondent how he evaluated the chatbot survey that he just completed compared to a classical web survey. 5 out of 11 replied better, for the others was indifferent (figure 81).
Most considered the chatbot survey was more engaging than their precedent experience with a web survey (figure 82).

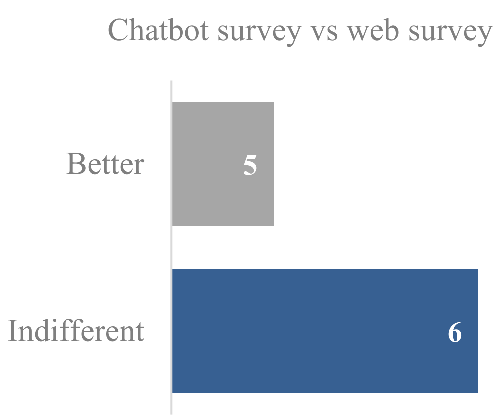


Figure 81

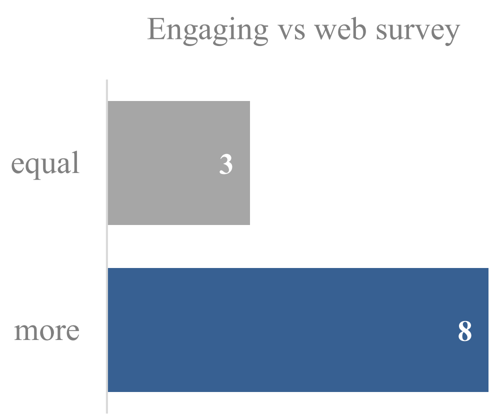


Figure 82

In addition, 6 out of 11 found it also less complex, while the other replied it was equal (figure 83). This last result contrasts with that of figure 80, where participants expressed a rate to the experience with the survey just completed. The discrepancy may be due to the difference between the two questions: one asked to rate the questionnaire just completed (figure 80), the other asked to compare it with a past web survey experience (figure 83).

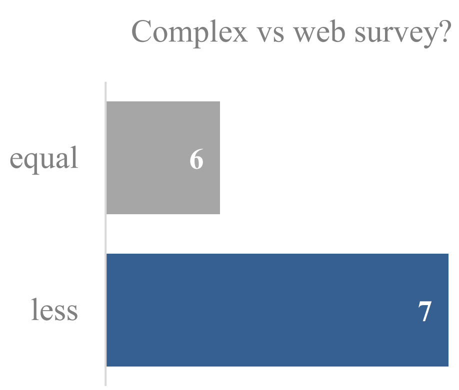


Figure 83

Comparison of satisficing answers between chatbot and web survey

I calculated the index of response differentiation Pd among answers to estimate the grade of satisficing behaviours of the two surveys. The index allows revealing the respondents' attention by measuring the variability of their replies: an active participant reads the questions carefully and does not give identical answers to save time. The index is determined by the following equation (Mccarty and Shrum; 2000):

$$P_d = 1 - \sum_{i-1}^{n} P^2{}_i.$$

Pi is the proportion of the values at a given point on the rating scale, and *n* is the number of rating points. Pd is equal to 0 when all respondents express the same rate, while it is close to 1 when there is high differentiation among the rates chosen.

The index is calculated considering answers to the Likert scale questions of figure 67-69-70-71-72. I have grouped these answers for the two types of survey, and I compute Pd between the rate of the replies for the chatbot survey and the web survey. Then, I compared the results with the Kim et al. (2019) research. In their study, they calculated the response differentiation of 106 teenagers to a questionnaire about Internet usage behaviour. Each questionnaire comprised 86 Likert scale questions. Their research uses a 2 (platform: web vs chatbot) × 2 (conversational style: formal vs casual) and randomly assigned the participants to one of the four conditions. They find that a chatbot survey with a conversational style got more differentiation between answers and thus fewer satisficing behaviours than all other conditions.

In this thesis, I compared only the web survey with a formal conversational style and the chatbot survey with a casual conversational style.

The results agree with that of Kim et al. (2019), as the index of response differentiation of the chatbot survey answers is higher than that of the web survey (figure 84). However, the difference is minimal compared to Kim et al. Moreover, we have to consider some limitations of this research because I collected only 15 answers from the chatbot survey that I have compared to the other 15 of the web survey. The sample is quite little to get accurate results that could be generalized. Furthermore, in this study, I can consider only the five Likert scale questions of each questionnaire completed because the others are multiple-choice questions.

Instead, Kim et al. (2019) have collected about 20 answers to the questionnaire for each of the four conditions (2 (platform: web vs chatbot) × 2 (conversational style: formal vs casual)), and a questionnaire individually has 86 Likert questions.

values	Fequency of rate of Web survey			
1	7	0,01	=(C63/$C$68)^2	I calculated the proportion of each frequency to the Total. Then I squared the result. Pd is the sum of the squares.
2	9	0,01	=(C64/$C$68)^2	
3	11	0,02	=(C65/$C$68)^2	
4	13	0,03	=(C66/$C$68)^2	
5	35	0,22	=(C67/$C$68)^2	
Total	75	0,708	=1-SOMMA(D63:D67)	**index of response differentation**

values	Frequency of rate of Chatbot survey			
1	1	0,00	=(C71/$C$76)^2	
2	9	0,01	=(C72/$C$76)^2	
3	14	0,03	=(C73/$C$76)^2	
4	22	0,09	=(C74/$C$76)^2	
5	29	0,15	=(C75/$C$76)^2	
Total	75	0,715	=1-SOMMA(D71:D75)	**index of response differentation**

Figure 84

Conclusions

Conclusion over **RQ2 (Could a chatbot survey be more effective than the classical web survey distributed with Google Forms?)** are:

- Participants enjoy more the chatbot survey than the web survey (figure 74-75). Indeed, the chatbot results to be more engaging because it adopts a conversational style that attracts the user. However, the participation with the Messenger link (modality b) was lower than that with the direct link to Google Forms. I assume it was because: some users prefer not to try new survey modalities, some for privacy concerns, and especially because some do not have Messenger.

- The chatbot led to slightly less satisficing responses. However, the difference is minimal, and future research with a more numerous respondents sample is recommended.

Conclusions and Limitations

I report the conclusions for the two research questions.

The research question one asks: RQ1**:** Was the adoption of the chatbot of the Department of Economics "Marco Fanno" positive in terms of reduction of the email received (RQ1.1), user satisfaction and potentialities of its features (RQ1.2), and economic impact (RQ1.3)?

RQ1.1: Did the adoption of the chatbot of Economics reduce the email received by the tutoring service?

The analysis of the number of emails received by tutors from 22 April to 30 July of years 2021-2020-2019-2018-2017 did not show clear evidence of the chatbot's contribution to reducing the number of emails received. Although in the year 2021, when the chatbot was adopted, there was a significant decrease in the number of emails compared to 2020, in 2019, when the chatbot was not present, emails were even lower. However, a contribution is plausible as it answered 107 questions considering the period 22 April - 30 July 2021.

The research limitation was the narrow period in which I could compare the number of emails. The 22 April to 30 July period was chosen due to the recent adoption of the chatbot (22 April 2021) and the latest available tutor report reporting until 30 July 2021.
A future investigation with a longer period (1 year) is recommended.

RQ1.2: What do students think about the chatbot of Economics? Do they appreciate the chatbot? What function do they like the chatbot could add?

Students manifested quite an appreciation for the chatbot with an average rating of 3.41 out of 5.
Among the problems reported in the questionnaire, 48% of the participants reported that the chatbot did not understand their question or was unable to answer. I presume the problem refers in particular to the open question and not to the interaction modality with the predefined options.

The feature most preferred by the respondents who would like the chatbot to have is the sending of push notifications that remind them of deadlines such as the payment of the university fee and the application for benefits (average rating of 4.45 out of 5).

They also like to receive notices of job offers/internships in line with their study plan (average rating of 4.28 out of 5). They also appreciate that the chatbot can give orientation suggestions (e.g. choice of field of study, study plan, optional courses) based on the preferences expressed to the chatbot through some aptitude questions (average rating of 3.89 out of 5).

RQ1.3: What is the economic impact of the chatbot on the Department of Economics?

I estimated a positive economic outcome from the chatbot adoption.
The forecasts showed an ROI of 29% over three years. I estimated that the costs outweigh the benefits in the first year of the chatbot adoption, while the benefits become higher than the expenses from the second year. The benefits are the savings generated by the chatbot and mainly the slight increase in subscriptions that it could bring. I have estimated a present value of net benefits of €2473 over three years and the break-even point in the third year.

The research limitation could be the assumptions on the estimation of the enrolment rate increase that was based accordingly to other universities adopting a chatbot.

RQ2: Could a chatbot survey be more effective than the classical web survey distributed with Google Forms?

The comparison of the results of two survey modalities - chatbot and web survey - confirm the findings of Kim et al. (2019). Respondents find more pleasant the chatbot survey than the web survey. Also, chatbot survey answers show more variability than replies of the web survey, thus denoting less satisficing. However, I found a minimal difference: the Index of response differentiation of the chatbot survey answers was 0.715 compared to 0.708 of the web survey answer.

The research limitation was the small sample of interviewees who participated in the comparison of the two types of survey. The other limitation was the small number of Likert questions were used for the comparison.

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