Marketing Decisions: The Influence of Artificial Intelligence on the Management Decision Process

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Management decisions have always been marked by a lack of rationality. Ensuring the rationality of management is the main goal of management control. This paper shows how algorithms and artificial intelligence influence the control loop of marketing decisions. Opportunities as well as limits of using this new technology for marketing are presented – along with the resulting necessary shifts regarding the area of marketing management control.

Keywords: marketing decisions, marketing management control, decision behavior, artificial intelligence, marketing automation, learning.

1 Marketing decisions: Control loop and rationality deficits

The control loop of marketing decisions can be outlined as follows, based on the St. Gallen Management Model (Ulrich/Krieg 1983) and literature on management control (Weber 1999 and Weber/Schäffer 2016, Reinecke/Janz 2007) (see Fig. 1).

1) Information supply: Before a decision is made, it is critical to provide sufficient information as a base for it. Improving the level of information is a central and ultimately the original function of management control (Horváth 2011).

On the one hand, external information about customers, competitors, sales intermediaries and influencers, but also about society, technology and politics is relevant. In marketing, this information is often provided through *market research*. On the other hand, management must be provided with internal company data, for example from human resources, production, logistics, but especially from *accounting*. Historically, the latter has been a major bottleneck in marketing (keywords: contribution margin accounting, cost unit accounting, pre- and post-calculations).

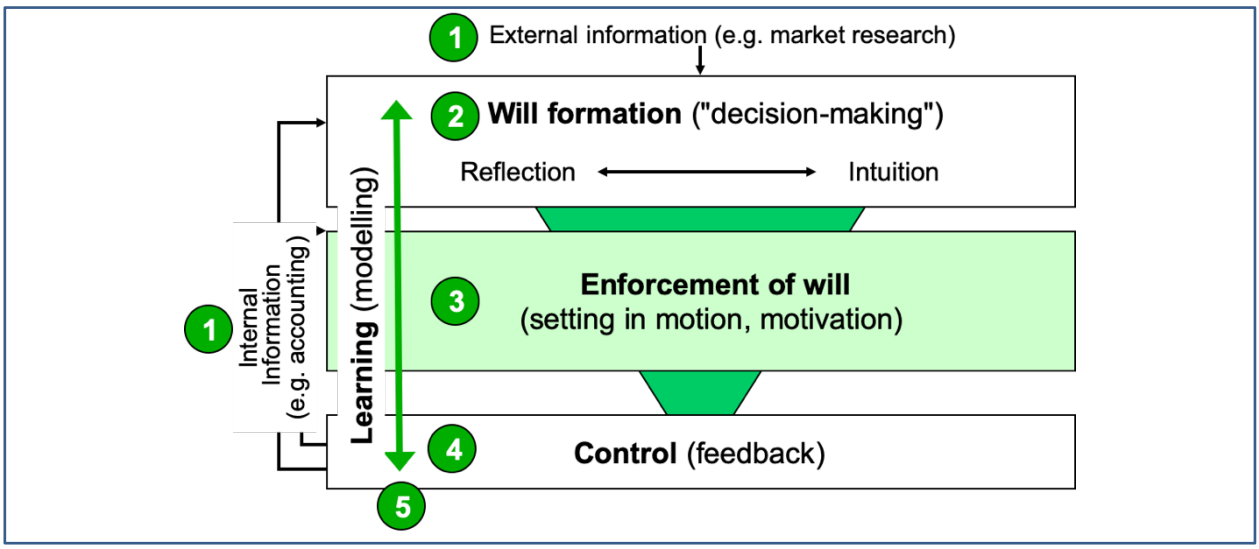

Fig. 1: Marketing decisions - the control loop

Source: own figure based on Ulrich/Krieg 1983, Weber 1999, Reinecke/Janz 2007.

2) Will formation: The will formation is the actual decision-making function and thus one of the most important management tasks. On the one hand, decisions can be based on planning, following standard reflective practices. The rational information processing procedure of planning is defined as a "systematic, future-oriented assessment and determination of goals, measures, means and ways of achieving future goals" (Wild 1974, p. 13).

The second source of decision-making is the use of intuition by managers - in other words their instinct or "gut feeling".

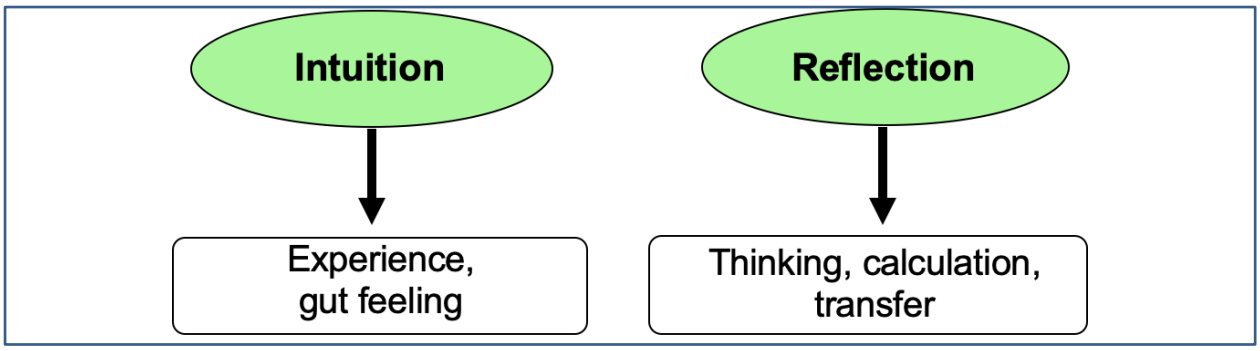

Fig. 2: Development of wills in marketing & management

Source: own illustration.

In recent years, there has been an intensive discussion in the field of decision-making behavior as to whether intuition should be seen as a heuristic that contributes to fast and efficient decision-making (Gigerenzer/Hertwig/Pachur 2011, Luan/Reb/Gigerenzer 2019), or whether intuition rather tends to lead to decision deficits ("biases") and thus to non-rational decisions (Tversky/Kahneman 1974; Kahneman 2003).

3) Enforcement of will: Strictly speaking, the execution of activities is not an actual management task, but the "setting in motion" (Ulrich/Krieg 1983) and thus the motivation of those entrusted with the execution. In this respect, there is a close connection to personnel management ("leadership").

4) Control: Controls are the comparison of an actual state with a specified target (Weber/Schäffer 2016, p. 270). In most cases, targets only make sense if they are controlled - and controls only make sense if they are backed by consequences. Applied to marketing, this means: Marketing control is hardly possible without marketing planning, and marketing planning without control is largely meaningless (see also Böcker 1988, p. 22).

A clear bottleneck in marketing planning and control lies in the fact that in the field of marketing, executives often plan instruments, but not goals or results. Marketing objectives are very rarely clearly operationalized as follows: "Increase (target direction) within 1 year (time reference) the unaided awareness (target type) of brand Y (object reference) from 20% to 35% (target extent) in group X (target group)." This makes effective control difficult.

A further challenge is the increasing potential of so-called "(Key) Performance Indicators (KPIs)", which often lead to an unstructured muddle of metrics from different sources (e.g. Google Analytics, Facebook, electronic image time measurements, contact data). The selection of relevant key figures remains a bottleneck both in general management (Siegwart/Reinecke/Sander 2010) and in marketing (Reinecke 2004).

5) Learning: This aspect of the decision-making process describes the use of control information to optimize the basis for future decision-making processes. It is therefore a matter of reviewing, on the one hand, the approach and decision-making methodology and, on the other, the design of competencies and incentives as well as personnel selection, deployment, and development for the future. This means that management and execution must be optimized by creating the necessary personnel and organizational conditions.

"Learning is not automatic. It requires a systematic examination of our experience." (Russo/Schoemaker 2002, p. 198 f.) From the author's point of view, this is the area in which the greatest deficit of traditional marketing management lies. Real learning processes are rare in many organizations: On the one part, this is due to the great variety and dynamism of the environment, and on the other part to the fact that marketing managers very frequently change jobs, particularly

in listed companies, and there is therefore insufficient continuity of personnel. However, the latter is an important prerequisite for learning processes "on the job". If a decision-making process is not repeated several times, for example, because a leading B2B trade fair only takes place every three years, then learning processes are limited, especially if they are not systematically recorded and used.

With this crucial deficit, the potential of information technology and especially of algorithms in marketing is very promising, as will be shown below.

2 Changes in the marketing decision process due to artificial intelligence

With regard to artificial intelligence, three basic evolutionary stages can be distinguished (Wirth 2018; similarly, also Kaplan/Haenlein 2019, p. 19): narrow, strong, and hybrid artificial intelligence. Narrow artificial intelligence is limited to a certain task (e.g., playing chess or optimizing prices in marketing) and cannot be extended to other tasks without human intervention. Strong artificial intelligence does not yet exist; it would be as powerful as human intelligence in the sense that it could solve new problems without human intervention. Most attention is currently focused on hybrid artificial intelligence, a hybrid form, which aims for the machine to be able to adapt independently to new challenges. Without going into the comprehensive overall scientific discussion on artificial intelligence at this point, the special feature of artificial intelligence is that these solutions are (increasingly) capable of learning to structure, substantiate, predict, and plan knowledge (Wirth 2018, p. 436).

2.1 Data Analytics Maturity Model

The Gartner Data Analytics Maturity Model (2016), which is premised on Davenport/Farris 2007, is a suitable model for illustrating the stages and effects of marketing analytics, albeit a simplistic one. A total of four levels are distinguished:

1) Descriptive analytics: This is about answering the question of "What happened?". In marketing, classic descriptive market research, such as the development of market sizes and shares, image, attitude and satisfaction measurements, is paramount.

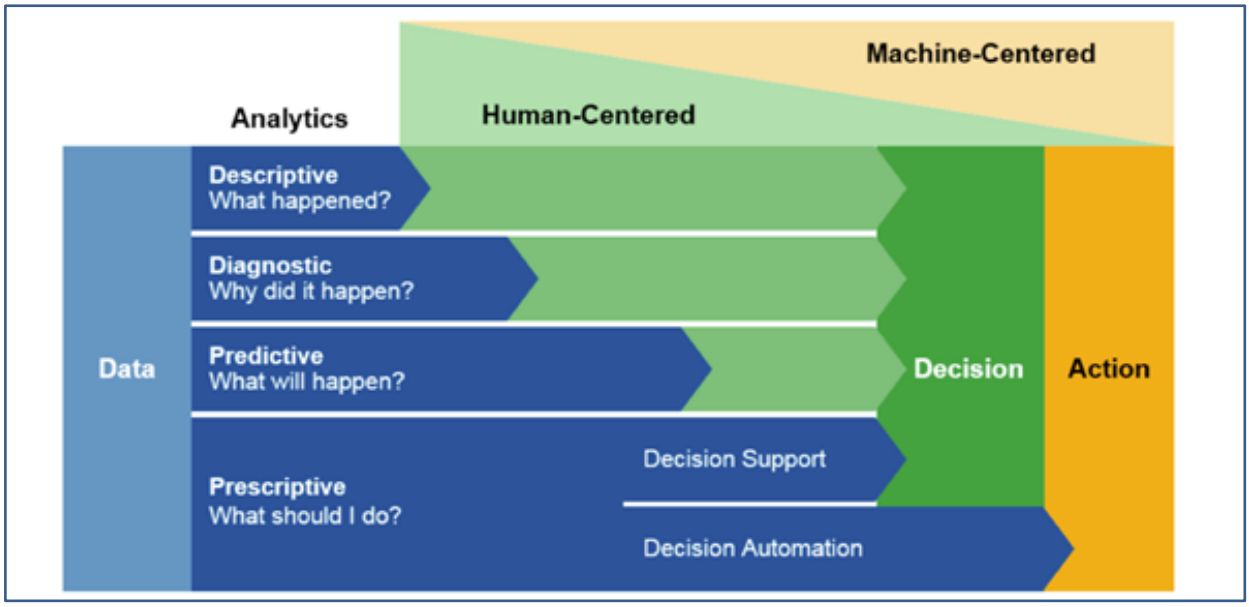

Fig. 3: Four levels of analytical capabilities

Source: Gartner 2016.

2) Diagnostic analytics: The focus here is on the "why", i.e., the explanation of cause and effect. Such a proof of causality is often done by experiments, in marketing for example A/B tests of websites or direct mails. Strictly speaking, four prerequisites must be fulfilled to prove a genuine cause-and-effect relationship (Kuss/Wildner/Kreis 2014, p. 35 f.):

- The two characteristic expressions, between which a theoretical relationship is assumed, vary together;
- The variation of the "reason" precedes the "effect" in time;
- Theoretical justification of the causal link (Hunt 2002, p. 127 f.);
- Alternative explanations can be excluded.

However, marketing practitioners are often content with the first two conditions being satisfied - for example when conducting A/B tests.

3) Predictive analytics: At this stage, the analyses are used to estimate or predict other data based on available data (see Agrawal/Gans/Goldfarb 2018 for details). This can be a simple extrapolation of data, for example the prediction of demand or price development based on a linear regression calculation - or more sophisticated models that help, for example, to predict the probability of default of creditor repayments or to estimate the recommendation potential of an influencer in the social media based on its previous follower structure and behavior.

The quality of the predictions ultimately depends on three aspects: the quality and quantity of the input data, the computing power, and the model quality. While computing power used to be a central bottleneck for forecasting, today the availability of relevant data is often the actual limiting factor. If the data basis is insufficient in terms of quality and quantity, there is a risk of misprediction (see Gigerenzer 2014 for details).

4. Prescriptive analytics: While the previous stages were limited to data analysis, this is the first stage of decision support. The model recommends actions that are suitable to achieve a specific (one- or multidimensional) goal - for example, which target groups are to be served with a mailing in order to optimize response rate, turnover or contribution margin (or all at the same time). Such expert systems were intensively discussed, for example, in the 1990s in the field of advertising (Esch 1998), even though they were not (yet) able to assert themselves at that time (see also Lilien 2011, pp. 197 on the advantages of marketing decision systems).

2.2 From decision support to automation of the marketing decision process

Prior to the introduction of information technology, managers in a company carried out the entire marketing decision process themselves, supported where necessary by accounting, management control, and market research functions. Information supply, will formation, enforcement of wills, control and learning processes were the responsibility of the individual.

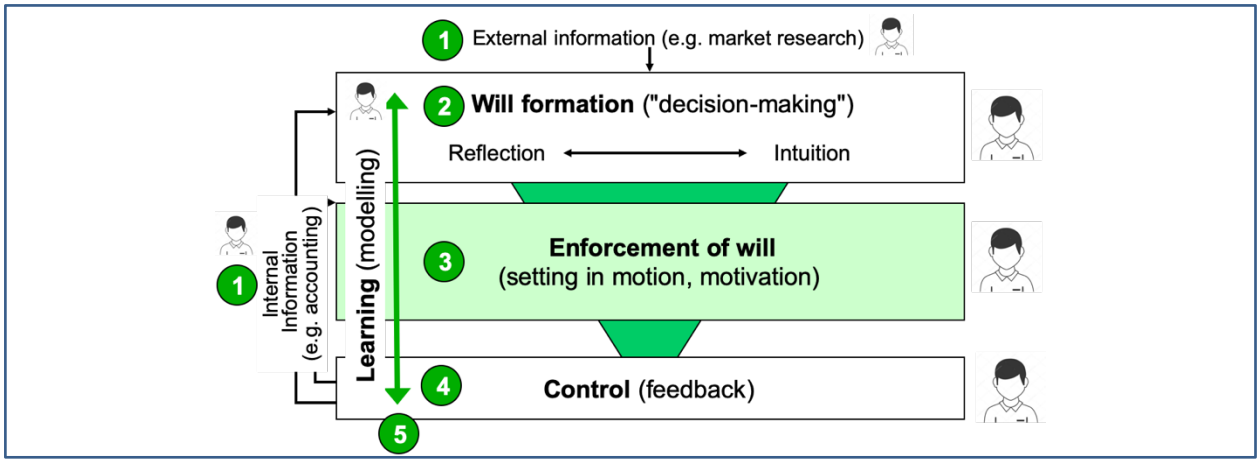

Fig. 4: Fully human-based marketing decision process

Source: own illustration.

The internal and external information supply areas (1) have changed dramatically in recent years. About 25 years ago, Peter Drucker saw the risks of information technology in its inward directedness - he lamented the degenerative tendency of information technology "to focus inward on costs and efforts, rather than outward on opportunities, changes, and threats" (Peter Drucker,

quoted by Davenport in Baker 2014). However, the big data discussion of recent years has shown, particularly in marketing, that a great deal of data originates from external sources and can be integrated into the planning process - be it from social media, macroeconomic studies or even weather databases. Therefore, not only marketing accounting based on internal IT systems is now (almost) fully automated, but also a large part of market research. There are probably few industries that have been as severely affected by digital disruption as market research. Whereas in the past comprehensive, regular tracking studies and industry analyses, often based on large, representative surveys, dominated, today rather agile, highly automated ad hoc experiments such as A/B tests and (click) behavior studies as well as customer journey analyses are common (see Reinecke/Wortmann 2018 for critical remarks). The automated part of the internal and external information supply of marketing has thus greatly expanded.

The same applies to control (3). Many marketing decisions, such as those concerning the optimal mix of advertising media, can be automated and in some cases even be controlled online without the need for intervention by marketing executives. In the case of self-learning systems, feedback control, which takes over the verification of the achievement of the target, can be carried out based on the target values of the original marketing decision. Building on this, a learning process (4) can be started to update and optimize the information base and algorithms for future marketing decisions. This modelling can be supported by the computer or even be refined and improved automatically. In the extreme case of artificial intelligence, self-optimizing modelling is conceivable.

Nowadays, there are very data-intensive areas (e.g., programmatic advertising) where computer-aided models develop suggestions that are superior to human decisions. Similar to car navigation systems, the model suggests decisions ("routes") that can then be adopted by humans. The more often the person follows the proposed decisions, the more urgent the question arises: Why does the human actually still have to decide, when the computer can already make an ("optimal") suggestion? This is particularly true if the computer has a better information supply than humans could process (analogous to the navigation system, where Google Maps, unlike the driver, has up-to-date online congestion information and traffic forecasts).

Therefore, if the will formation (2) and - especially in the case of online decisions - the enforcement of the will (3) are also automated, then in extreme cases the entire marketing decision process is automated (see Fig. 5).

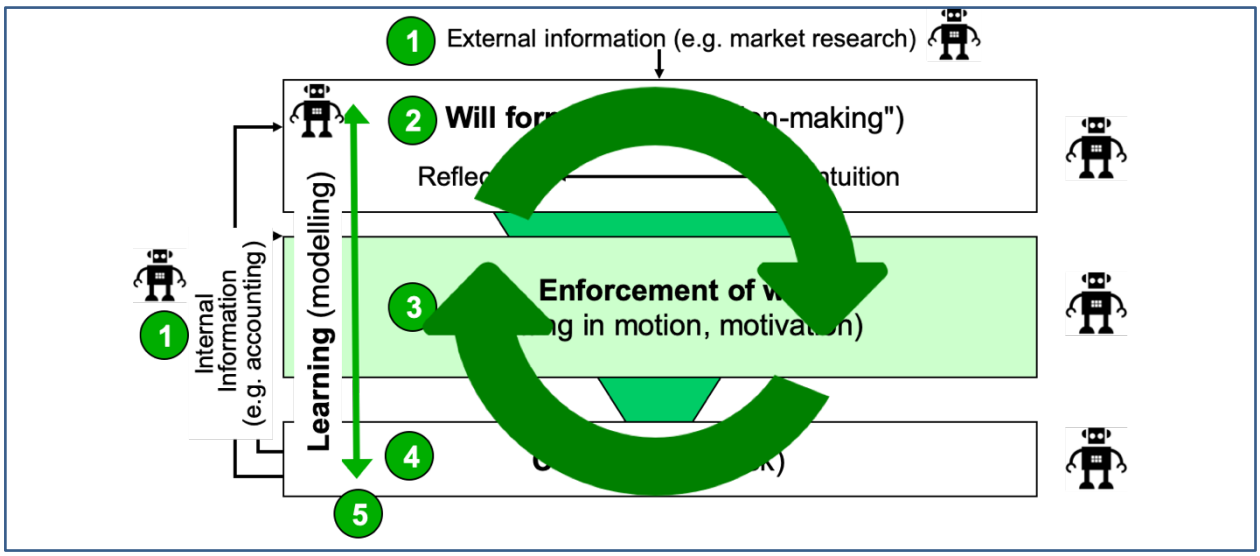

Fig. 5: Fully automated marketing decision process

Source: own representation based on Wu 2018.

Even if such a complete automation of marketing decisions is (currently) not yet widespread, a decisive advantage over the classic, human-based decision-making process is evident. The central bottlenecks in the human decision-making process are the speed of processing and the ability to learn. In other words: The entire marketing decision-making process takes a lot of time and the process is not run through very often, so that the knowledge base and thus also the applied decision models are only of limited quality. The computer, on the other hand, can run through the entire process very quickly and very frequently and thus "learn" much better, i.e., adapt its underlying model or algorithm. In extreme cases, the computer is able to simulate an almost infinite number of decisions and estimate the effects. Just like a "learning" chess computer can play significantly more chess games in a short time than a human can (and thus can learn faster), a computer-supported programmatic advertising can produce faster and better advertising budget decisions than a marketing executive. The same applies to an address selection of target groups by means of data mining in comparison to (limited) intuition-supported procedures of experienced marketing executives.

An interim conclusion can be drawn: If most steps of the marketing decision process can be automated, then computer-aided models will be superior to human decision making in the future. The reason for this is the limited information processing capacity and learning ability of humans. However, a central prerequisite for this automated decision-making process is that on the one hand the corresponding data is actually available in all steps. On the other hand, the decision-making process must be very structured.

3 Increased marketing efficiency and effectiveness through the use of marketing algorithms

In marketing reality, more and more application areas are emerging in which artificial intelligence can help to increase either marketing efficiency or even marketing effectiveness.

As the previous discussion has shown, so-called artificial intelligence will be used in marketing, especially in data-intensive, highly structured processes. Davenport and Kirby (2016) summarize this as follows: "The more structured tasks will be taken over by machines, or made substantially more productive by them."

The increased use of information technology and the availability of data will significantly increase *marketing efficiency* in many areas. For example, data acquisition can be facilitated by voice-controlled systems or sensors. Many processes and routine tasks can be automated: Chatbots can be used both online and over the phone (self-learning), and handle the majority of frequent and typical customer enquiries. Such automated "first-level customer support" increases efficiency in operational marketing because employees can focus on the more demanding activities.

Furthermore, it will be possible to eliminate certain intermediate process steps in many marketing activities. When using programmatic advertising, media agencies are often eliminated and two or three-stage distribution channels are converted to direct sales, which means that certain logistics as well as wholesale and retail tasks are no longer necessary.

Figure 6 shows marketing activities that have high potential for increasing efficiency due to automation.

But not only the marketing efficiency, but also the *marketing effectiveness* and thus the efficacy can be increased by the use of algorithms. Numerous decisions and actions are only possible through intensive and fast marketing automation. This applies, for example, to the screening and monitoring of social media, comprehensive media sentiment analyses, facial recognition of customers or offering simultaneous written or oral translations in customer contact. Real-time targeting in online marketing, as part of which dynamic and possibly even personalized content is presented to target customers at the right time, would also be inconceivable without marketing automation. The same applies to the optimization of non-payment risks or situational price differentiation.

Characterization of marketing activities	Examples of affected marketing areas
1) Automation is already partially in use	Online marketing, logistics, call centers
2) Low physical/human contact	Industries: telecom & financial services
3) Easy transfer of information	Sales support, market research, training
4) Information analysis	Market research, marketing analytics
5) Data related questions	Media planning, CRM, marketing accounting
6) Quantitative analyses	Online advertising, data mining
7) Simulations, virtual reality	Trade fairs, event management, sponsoring
8) High consistency requirements	Industries: security, pharmaceuticals, transport, banks
9) Clearly defined working rules	Standard field sales, logistics

Fig. 6: Examples of marketing activities with high efficiency enhancement potential through automation

Source: based on Davenport/Kirby 2016.

With Wilson/Daugherty (2018, p. 121 ff.) it can thus be ascertained that artificial intelligence offers companies five central potential benefits: Flexibility, speed, data processing capacity, decision making, and personalization.

4 Limits of the automation of marketing decisions

In light of the efficiency and effectiveness enhancement potential of marketing automation and the so-called artificial intelligence in marketing, the question arises as to how marketing discipline will develop in the future - and whether, for example, the kinds of marketing executives are still needed who are trained or have been trained to date.

First, it must be emphasized that the complete automation of the decision process is so far only possible invery limited situationsframework, because on the one hand many processes are not sufficiently structured and on the other hand the data are not available in the necessary form or cannot be collected. As the course of industrialization and digitization in recent decades has already shown, technology will always change many task profiles, eliminate individual activities, and at the same time open up new fields. Even if technical progress is very rapid, the individual remains a social being that needs time to adapt change. The latter becomes obvious when one

considers how gradually and successively media usage patterns have changed in recent decades. Most traditional media still exist, but they have been supplemented and partially replaced by new, mostly digital media.

Despite the enormous potential of algorithm-based decision processes in marketing, there will still be a large number of decisions, activities and requirements in the coming years and decades that show the (current) limits of this technology:

1. Reacting to rare events & exceptions: Artificial intelligence usually requires large amounts of data; these are not available for some decisions - or occur so rarely that it is not worth programming an (possibly learning) algorithm, because repetition is rare and, therefore, no real learning process is possible. For example, if a company only serves European customers, the system may not be able to respond to different buying habits and preferences of Asian customers. Thus, such decisions will continue to be made manually in the future for reasons of economic efficiency.

2. *Sensorimotor activities and decisions:* In some industries, there are many marketing-related decisions that cannot yet be automated but are very critical to success. For example, the tactile assessment of fabric quality in the (luxury) fashion sector is still carried out manually - the computer can aid but cannot yet take the decision. Even creative processes such as design decisions by fashion designers or advertising creation can hardly or only to a limited extent be automated.

3. Justifying decisions in a comprehensible manner: For example, if prices have been optimized using algorithms, the question arises as to whether companies are able to explain price increases for certain customer groups. This challenge incorporates both ethical (e.g., equal treatment) and legal aspects (compliance). The same applies, for example, to the decision as to whether a certain customer may pay on account - or whether he must always pay in advance. In many cases, decisions must be transparent and explainable afterwards. It is neither ethically nor legally permissible for personal decisions to refer to the fact that the computer made the decision and is "responsible" for it. However, it is very difficult to explain the automated decisions based on complicated algorithms in an understandable way.

4. Real "understanding" and interpreting: Algorithms can learn to copy human behavior, but by nature they are always "rational" - even if they imitate some irrational human behavior and decisions. Genuine emotional intelligence, compassion and a real understanding of the customer's situation cannot even be expected from artificial intelligence. However, there is a noticeable

difference for the customer as to whether one pretends to be interested or friendly, or whether one actually is. Therefore, interpersonal personal sales will continue to occupy a prominent position in the marketing mix in the future, as they cannot be fully automated. A further complicating factor is that even if people (customers or managers) recognize that an algorithm produces better decisions, they still trust a person rather than artificial intelligence (Dietvorst/Dimmons/Massey 2014, p. 124 f.). In particular, people overstate their own personal opinions (Logg/Minson/Moore, 2019, p. 96).

5. Real learning: Experiments such as A/B testings are an important tool in optimizing automated marketing decisions. However, such tests often lead to sub optima, not to optimum, depending on the selected start configuration (e.g., a web page). In order to reduce this danger, in reality, one tries to include as many start configurations as possible (e.g., very different websites) in order to cover the search space as broadly as possible and come close to the optimum. However, an important condition for real learning based on experiments is that one has a theory that is able to explain cause-effect - and one can exclude other causes (Hunt 2002, p. 127 f.; Kuss/Wildner/Kreis 2014, p. 35 f.). A/B tests and regression calculations alone are therefore not sufficient.

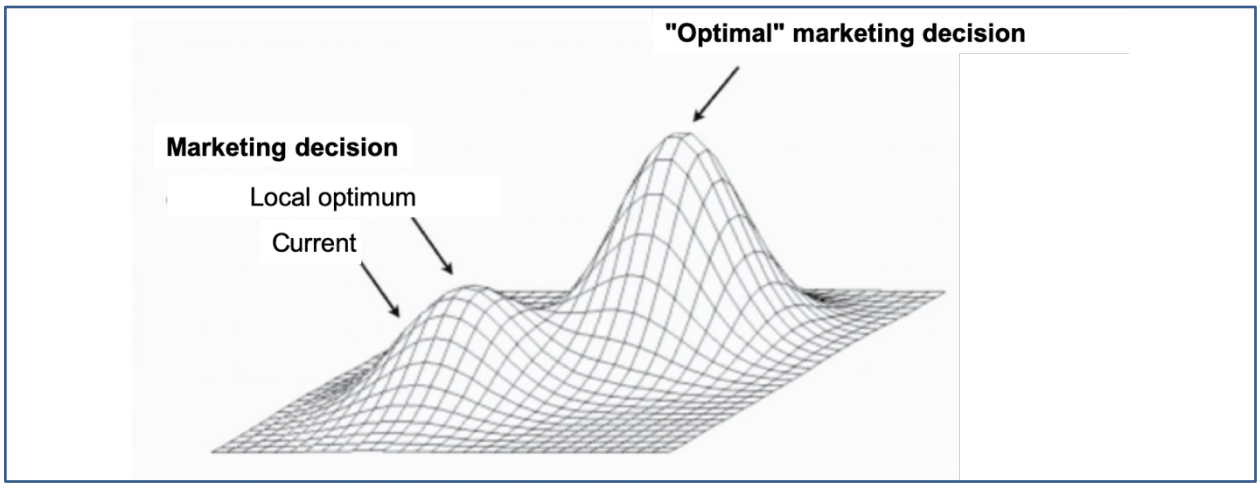

Fig. 7: Experiments do not always lead to optimal marketing decisions
Source: own representation.

6. Intentions: An algorithm cannot develop an intention, i.e., in particular the overriding objectives must first be set by the management. A computer cannot develop an intention of its own; for marketing, this means that goals and target priorities must be set (e.g., growth, profitability and security). Goal setting cannot therefore be automated and remains a management task.

7. Humor: Marketing is a social process, which also works with humor, irony and partly sarcasm. This is where algorithms are currently reaching their limits - not only in terms of correct

comprehension and interpretation, but especially in terms of generating humorous or ironic content. This is all the more true if many constraints (e.g., political correctness) have to be met.

5 Conclusion

Algorithms and artificial intelligence will strongly influence marketing decisions in the future. If marketing management control is seen as a quality assurance task of marketing management, it can be stated that automation can largely eliminate a decisive bottleneck in marketing management: The insufficient learning processes due to the limited information processing capacity of marketing management on the one hand and the too low number of repetitions necessary for optimization on the other.

For marketing management, this means that in the future it will be less the management's experience due to the repeated performance of certain marketing activities that will be decisive, but rather the development of a clear objective, emotional empathy as well as interpretation and theory formation that will stand in the foreground. In other words: While in the past the most important bottleneck of marketing will formation was primarily a lack of rationality due to an insufficient information base, automation strengthens the rational elements of the decision-making process. The deficit thus lies increasingly in the area of intuition. After all, it remains a central task of marketing management control to ensure the balance of intuition and reflection in decision-making - but the "human" aspect becomes more important.

Bibliography

Agrawal, A/Gans, J. S./Goldfarb, A. (2018): Prediction Machines: The Simple Economics of Artificial Intelligence, Boston (MA).

Baker, E. H. (2014): Looking Outward with Big Data, in: Tech & Innovation, originally published by Booz & Company, March 31.

Böcker, F. (1988): Marketing-Kontrolle, Stuttgart et al.

Davenport, T. H./Farris, J. G. (2007): Competing on Analytics: The New Science of Winning, Boston (MA).

Davenport, T. H./Kirby, J. (2016): Only Humans Need Apply: Winners and Losers in the Age of Smart Machines, New York (NY).

Dietvorst, B. J./Simmons, J. P./Massey, C. (2015). Algorithm aversion: People Erroneously Avoid Algorithms After Seeing Them Err, in: Journal of Experimental Psychology, General, 144, 1, pp.114-126.

Esch, F.-R. (1998): Expertensysteme zur Unterstützung von Werbeentscheidungen, in: Hippner H./ Meyer, M./Wilde, K.D. (Hrsg.): Computer Based Marketing, Wiesbaden, S 97-107.

Gartner (2016): 2017 Planning Guide for Data and Analytics, Document G00311517, Stamfort (CT).

Gigerenzer, G. (2014): Risk Savy – How to Make Good Decisions, New York (NY).

Gigerenzer, G./Hertwig, R./Pachur T. (Hrsg.) (2011): Heuristics: The Foundations of Adaptive Behavior, New York (NY).

Horváth, P. (2011): Controlling, 12th edition, München.

Hunt, S. (2002): Foundations of Marketing Theory, Armonk (NY).

Kahneman, D. (2003): Maps of Bounded Rationality: Psychology for Behavioral Economics, in: American Economic Review, 93, 5, pp. 1449-1475.

Kaplan, A./Haenlein, M. (2019): Siri, Siri in my Hand, who is the Fairest in the Land? On the Interpretations, Illustrations and Implications of Artificial Intelligence, in: Business Horizons, 62, 1, pp. 15-25.

Kuss, A./Wildner, R./Kreis, H. (2014): Marktforschung - Grundlagen der Datenerhebung und Datenanalyse, 5th edition, Wiesbaden.

Lilien, G. L. (2011): Bridging the Academic–Practitioner Divide in Marketing Decision Models, in: Journal of Marketing, 75, 4, pp. 196-210.

Logg, J. M./Minson, J. A./Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment, in: Organizational Behavior and Human Decision Processes, 151, pp. 90-103.

Luan, S./Reb, J./Gigerenzer, G. (2019): Ecological Rationality: Fast-and-Frugal Heuristics for Managerial Decision Making under Uncertainty, in: Academy of Management Journal, Published Online, January.

Reinecke, S. (2004): Marketing Performance Management, Wiesbaden.

Reinecke, S./Janz, S. (2007): Marketingcontrolling - Sicherstellen von Marketingeffektivität und -effizienz, Stuttgart.

Reinecke, S./Wortmann, C. (2018): Google Knows it Better? Ein Plädoyer für integrierte und wider ausschließlich verhaltensorientierte Ansätze zur strategischen Kundensegmentierung, in Barth, B. (et al.): Praxis der Sinus-Milieus, Wiesbaden, S. 193-207.

Russo., J. E./Schoemaker, P. J. H.(2002): Winning Decisions: Getting It Right the First Time, New York et al.

Siegwart, H./Reinecke, S./Sander, S. (2010): Kennzahlen für die Unternehmensführung, 7th edition, Bern et al.

Tversky, A./Kahneman, D. (1974): Judgment under Uncertainty: Heuristics and Biases, in: Science, 27, pp. 1124-1131.

Weber, J. (1999): Einführung in das Controlling, 8th edition, Stuttgart.

Weber, J./Schäffer, U. (2016): Einführung in das Controlling, 15th edition, Stuttgart.

Wild, J. (1974): Grundlagen der Unternehmungsplanung, Hamburg.

Wilson, H. J./Daugherty, P. R. (2018): Collaborative Intelligence: Humans and AI Are Joining Forces, in: Harvard Business Review, July-August, pp. 114-123.

Wirth, N. (2018): Hello marketing, what can artificial intelligence help you with?, in: International Journal of Market Research, 60, 5). pp. 435-438.

Wu, M. (2018): Artificial Intelligence - unpublished presentation at Lithium, San Francisco (CA).