A Value Framework for Technology Potentials: Business Adoption of Emotion Detection Capabilities

Stefan Koch, Johannes Kepler University Linz, Austria*

Kemal Altinkemer, Purdue University, USA

ABSTRACT

This paper proposes a modified approach for analyzing and presenting the value generation, capture, and distribution from organizational adoption of new technologies. The focal technology used is emotion detection, and technical approaches and possibilities as well as some of the inherent challenges and limitations are briefly described. For this technology potential, a novel framework for value generation, capture, and distribution is developed using a design science approach. The framework allows organizations to select appropriate adoption areas and derive methods for risk and problem mitigation. This framework is then demonstrated within the selected setting of emotion detection capabilities.

KEYWORDS

Business Value, Design Science, Emotion Detection, Value Generation

INTRODUCTION

Creating business value from information technology (IT) has been a topic discussed for decades (McAfee & Brynjolfsson, 2008). Kohli and Grover (2008) provided a good summary and additionally an outlook for this discussion, and also Melville et al. (2004) reviewed the extant literature and proposed an integrated model for IT business value. The challenge of analyzing and selecting investment areas based on business value is extremely relevant, today, when the focus of many organizations is on digital technologies and on how to use them for transformation (Fitzgerald et al., 2014) and to find and exploit respective opportunities (Muehlburger et al., 2020). This paper aims at developing a framework supporting this strategic task.

One example for a digital technology that can offer several different application opportunities for organizations is emotion detection. Providing valuable decision-making data, current technology is starting to facilitate the detection and classification of human emotions, allowing to accurately measure levels of happiness, sadness, and other emotional states through video, photo, voice, gesture, text, any other sensor data or a combination thereof. This has led to rising interest in emotion detection in popular culture and media. However, while emotion detection could be used in pricing, advertising, service management, and many other areas, adoption by business organizations has been comparatively
lacking, thus far. This means that, in an age of digital transformation, organizations face the challenge
to decide whether to adopt and how and which particular areas or application contexts to adopt such
a new technology; as a result, organizations need support for such tasks.

Current uses can be broadly divided into two categories: 1) Real-time applications that do not
store emotions and are mostly related to human-computer interaction; 2) applications that record
emotions for later analysis. Within this second group, further classification can distinguish between
anonymous data collection (e.g., for user interface design improvement) and individually attributable
data collection. Importantly, the last category enables one-to-one marketing based on emotions.
Companies have already implemented, or are close to implementing, programs that capture and
leverage emotion data, including: Attention monitoring for ad effectiveness; TV ratings via facial
micro-expression analysis and eye tracking; call routing in call centers based on customer anger via
voice pitch analysis; recommendation services, especially for entertainment; increasing security at
malls, airports, sports arenas, and other public venues by detecting malicious intent; creating enhanced
virtual reality experiences; accommodating different learning styles in educational environments;
drowsiness detection in transportation; monitoring emotions and communication based on skin
conductivity via sensors for autism patients or pain management for children patients via facial
analytics in medical settings. Chen, Chang et al. (2017) provided an overview of advantages for
the context of emotion classification of YouTube videos, listing search results, recommendations,
advertisement accuracy, policy adjustment, and Web intelligence. Lee et al. (2012) used the valence
and arousal of Facebook users to explain event intentions. Mukhopadhyay et al. (2020) in the context
of online learning.

This paper aims to propose a novel framework for value generation, capture, and distribution to
allow organizations to select appropriate adoption areas and methods for risk and problem mitigation,
illustrated using the technology of emotion detection. Recognizing the potential value or opportunities
(Muehlburger et al., 2020) that emotion detection capabilities could provide for a larger business
context, this paper describes the fundamentals of emotion detection, including its inherent challenges
and limitations to illustrate the setting. This process is framed as design science research; the theoretical
contributions of this paper extend beyond the scope of emotion detection, as the framework the
authors present can be applied to the adoption of new technologies in general. Thus, this research
contributes to both the domain of emotion detection, but, more importantly, to the wider discussion
on business value of IT (McAfee & Brynjolfsson, 2008) and digital transformation of organizations
through new technologies (Matt et al., 2015; Muehlburger et al., 2020; Nan & Tanriverdi, 2017). First,
the authors will present the background on both business value from IT and emotion detection. Then,
they will discuss the research framework. Subsequently, the researchers will describe the framework
design as well as demonstration in the chosen context. Finally, they will conclude with a summary,
limitations, and future work.

BACKGROUND AND LITERATURE REVIEW

Business Value from Information Technology and Digital Transformation

In the last years, the understanding of the role of IT and of the way it adds to organizational value
creation has evidenced a shift from a more supportive and reactive towards an enabling and proactive
function. Already in 2003, Sambamurthy et al. presented a new conceptualization of the role of IT
in contemporary firms. Their call for a role more focused on shaping was based on the assumption
that the logic underlying strategy was shifting. They argued that strategies following the logic of
positioning and leverage were losing relevance in increasingly turbulent and innovation-driven
markets. In Sambamurthy et al.’s (2003) view, an opportunity-based logic of strategy is necessary,
focus on continuous innovation and the ability to coevolve assets, capabilities, and knowledge
as better suited for organizations in fast changing environments. Nan and Tanriverdi (2017) further
elaborated on the role of IT for changes in market logic. They identified technological developments and their inclusion in organizational practice as core drivers for competitive advantages. The resulting market situations with competitive advantages being generated and eroded by new ways of IT usage within organizations are labeled as hyper-turbulence. Such hyper-turbulent innovation-driven markets represent the fast-changing environments in which this logic of opportunity gains relevance. This increased need to identify and utilize new technology-based opportunities has been a core driver in the rise of the role of the Chief Digital Officer as supplement to the traditional role of the Chief Information Officer, with a strong focus on exploring IT-enabled innovations and associated strategic opportunities as a core task of Chief Digital Officers (Horlacher & Hess, 2016; Urbach et al., 2019). New strategic frameworks also show a strong emphasis on the identification of potentials due to new technology. As Matt et al. (2015) pointed out, traditional IT strategies focus on the management of IT infrastructure within a company and therefore, to some degree, restrict product- and customer-centric opportunities arising from new digital technologies. Digital transformation strategies on the other hand use a more business-centric perspective and focus on transforming products, processes, and organizational aspects through the application of new technologies (Matt et al., 2015).

However, this requires innovative methods to evaluate these new technologies (Bergeron et al., 1991), such as starting with organizational goals and critical success factors (Peffers & Gengler, 2003) to then evaluate different applications of a particular technology (Renkema & Berghout, 1997). Therefore, in this paper, the authors propose a new framework to group the different uses of emotion detection technologies, potentially uncover additional ones, and link them to the business value generated. Past approaches to grouping, evaluating, and, to some degree, graphically plotting applications were mostly based on using a two-dimensional matrix. Most frequently used approaches employ risk vs. benefit or value to the business comparisons (Jeffery & Leliveld, 2004; Parker & Benson, 1988). Other proposals have used external vs. internal as criteria (Notowidigdo, 1984), or group around stages in the customer life cycle (Ives & Learmonth, 1984). Tjan (2001) proposed fit and viability as axes, again in a two-dimensional representation that allows for strategy or decision derivation. None of these approaches has found widespread use or acceptance within the discussions surrounding digital transformation, highlighting the need for adapted frameworks that are more in line with current problems and thinking.

TECHNOLOGY FOR EMOTION DETECTION

Emotions and Emotion Detection

Emotions are central to human experience and influence cognition, perception, attention, learning, and communication. While the literature provides multiple definitions of emotion, it is generally accepted that an emotion is comprised of psychological and physiological changes in response to a stimulus. Ekman’s (1984, 1992) seminal work on emotion and its expression initially provided six categories of basic emotions: Anger, disgust, fear, happiness, sadness, and surprise. Later, he expanded this list to include amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame. A further distinction can be made between primary emotions, which are limbic-accompanying physiological and physical changes, and secondary, cortical emotions, which can be triggered by cognitive processes. Also valence and arousal are important aspects in emotion detection (Basu et al., 2015).

Other research areas that have focused on emotions include cognitive and behavioral sciences, particularly Simon’s (1959) groundbreaking works on decision making. In addition, affective computing has emerged, in which machines recognize and/or deliberately influence emotion or other affective phenomena (Picard, 1997). This field combines engineering and computer science with psychology, cognitive science, neuroscience, and other fields.

Researchers have used this growing understanding of human emotion and accompanying progress in technological capabilities to advance human-machine interactions. Facial emotion detection
has been applied to psychological and neurological disorders such as bipolar disorders, autism, Down syndrome or schizophrenia (Brown, 2017; Cebula et al., 2017; Sharma et al., 2017). Today, technological solutions for capturing emotions have progressed to a level that allows for use in more standard and real-world applications. For example, smart homes are being designed to operate based on facial emotions (Chen, Yang et al., 2017). While the specific technologies in these applications differ, they generally enable a device to accurately measure levels of emotions such as happiness and sadness. The fundamental differences in current offerings can be categorized according to the input data used, which can be video, photos (Bartlett et al., 1999; Dagar et al., 2016), voice, gestures, touch interactions on smartphones (Ghosh et al., 2019), text (Chen, Chang et al., 2017), any other sensors or a combination of several such elements. Electroencephalogram signals have been used to detect continuous facial emotion (Soleymani et al., 2016) and Kinect 3D facial points are also used for facial emotion detection (Zhang et al., 2016). The progress in such technologies is also evidenced by the recent increases in commercial ventures (Dwoskin & Rusli, 2015). For example, the company Affectiva (https://www.affectiva.com) has grown out of the MIT Media Lab to use facial cues or physiological responses to significantly advance artificial intelligence for multiple applications. Also startup Emotient has developed an artificial intelligence solution based on analyzing facial patterns. Further proof of potential of emotion detection is the interest from large technology companies, exemplified by Apple’s acquisition of Emotient, Microsoft’s Project Oxford and emotion recognition API for analyzing images now embedded in Azure Cognitive Services (https://azure.microsoft.com/services/cognitive), and IBM textual emotion detection on the Watson cloud (https://www.ibm.com/cloud/watson-natural-language-understanding). Further emotion recognition APIs currently available also include EmoVu, Nviso, Kairos, Face Reader by Noldus, Sightcorp, SkyBiometry, Face++, Imotions, CrowdEmotion, FacioMetrics, Text to Emotion Software, Receptiviti, Bitext, Mood Patrol, Synesketch, and Tone API.

Challenges in the Adoption of Emotion Detection

The previous examples provide strong indication of the potential opportunities emotion detection provides. However, for several possible reasons, emotion detection currently does not seem to be applied to a greater number of application use cases. The primary group of challenges hinges on the reliability of the different technologies and, to some extent, the reliability or consistency of underlying properties of emotions. By nature, emotions are multidimensional and transient, which creates problems for different applications. In some cultures, showing emotions is also less common or even frowned upon, and suppressing outward signs of them is therefore the norm (Ekman et al., 1969). This creates problems for detection technologies, especially if they are developed or calibrated within other cultures. On a more personal level, people are inherently different in the emotions and moods they experience, as well as in how they display them, which strongly relates to levels and scaling of emotion measurements. One person’s high level of anxiety might mean something different than another person’s. The mental accounting (Thaler, 1999) dictating how individuals act might play a role in how people assess an individual’s burst-out laughing vs. all-teeth smiling. Some of these assessments could be improved by individual historic data, but this might probably not be acceptable or reasonable for all applications. Finally, depending on the setting, users might start to try to hide or masquerade their emotions, with some people (e.g., those trained in acting) being more successful. In general, reliability can be increased by including multiple sensors for multiple information sources (e.g., face, gesture and voice), if the application allows it.

Besides reliability issues, customer perceptions, especially relating to privacy concerns, are a main roadblock to widespread use (Dwoskin & Rusli, 2015). Tying in with a general debate on who owns customer data, emotion data are highly sensitive and personal, especially surrounding emotions such as anger or grief. There are many examples of times when a person might not want their emotions to be seen or detected (e.g., when crying). Therefore, many users will be reluctant to share such data. Also, there will be differences in attitude towards divulging emotional state data, based upon whether
the application works in real-time or includes recording for later analysis, and whether identification of users is possible. Even in the case of real-time usage, some lingering doubts about possible storage by a provider, or fears about the data being linked to an individual having the emotions, might persist. Technology familiarity (Turner, 2008) will also likely affect customer perceptions and acceptance.

RESEARCH FRAMEWORK AND METHODOLOGY

For this research, the authors adopted a design science approach, as their main goal was to develop a framework to address a relevant business problem of value generation, capture, and distribution in the context of emotion detection, thus also contributing to increased successful adoption. Design science as a research framework for information systems research is concerned with building and evaluating artifacts, including software, conceptualizations or mathematical models (Hevner et al., 2004), including frameworks such as for the research at hand. Hevner et al. (2004) also highlighted the need for structured guidelines regarding the conduction of design science research, and provided guidelines for its practical application, including problem relevance, research contribution, as well as rigor. In 2007, Hevner (2007) clearly distinguished three design science research cycles, namely relevance, rigor, and design. Peffers et al. (2007) developed a six-step process framework for the application of the design science research method.

Based on these guidelines, the research process of this paper is as follows. First, the authors describe the problem and its relevance by focusing on the technology for emotion detection and related challenges in its adoption. This corresponds to establishing the problem relevance (Hevner et al., 2004), which the authors presented in the background section. Then, the researchers design and represent the framework as an artifact according to the respective guidelines (Hevner et al., 2004). The design is grounded both in the problem as well as prior work and theory, thus conforming to applying appropriate rigor (Hevner et al., 2004). The authors describe the design process and the resulting artifact in the following section. Afterwards, they detail a demonstration using a series of potential business applications from the problem context which serves as experimental evaluation (Hevner et al., 2004). The authors formed the basis by collecting application ideas from MBA students. In the following sections, they describe the data collection process, which took place in two vastly different countries, together with the results. Through this process, the authors address both the design and the rigor cycle of Hevner (2007). Based on Gregor and Hevner’s (2013) work, the contribution of this paper can be classified as exaptation, because the application domain of emotion detection is still in low maturity and the framework extends the knowledge of prior solutions. The research contribution lies predominantly in the design science research method (Hevner et al., 2004).

DESIGN OF THE APPLICATION VALUE FRAMEWORK

The authors designed the framework for this study based on prior research and knowledge. The main decision points concerned the aspects to be included, and the determination of the basic layout and number of axes, as well as the different criteria or dimensions to use.

As to the layout, the authors adopted a two-dimensional layout as established and easy to use, as a starting point; this is similar to prior approaches (Jeffery & Leliveld, 2004; Parker & Benson, 1988; Tjan, 2001). As to the axes, the authors chose Porter’s (1985) value chain, as it provides an easy to understand, common, and comprehensive way to look at different functions within a firm, and it is widely used. This also highlights the predominantly business-centric approach in line with digital transformation research (Matt et al., 2015). Therefore, the authors placed the core and support functions on one axis. If a higher level of detail is needed, it is possible to move to the level of business processes within a function. This would also help users in systematically checking for potential applications in each function. Given that the value generated by deployment in different functions can significantly differ between industries, it could be necessary to split between industries, at least
in some functions. The authors used viability, or risk, associated with the application as second axis, in line with most prior approaches (Jeffery & Leliveld, 2004; Parker & Benson, 1988). This captures both the technology risk in implementation at the time of analysis and the financial and adoption risk in the context of emotion detection, which is predominantly linked to privacy concerns.

The analysis of the literature revealed the value generated as a decisive factor. Therefore, as the value generated will naturally differ according to the application function and industry, is the authors included and denoted it by different sizes of circles in the appropriate positions within the matrix. Most importantly and extending prior approaches, depending on application opportunity, the value generated will not be evenly distributed to all players or participants. Some applications will predominantly benefit the user (e.g. through improved user interface) and only indirectly the firm (e.g., through increased satisfaction and repurchasing behavior). Notowidigdo (1984) had already proposed this differentiation (i.e., direct benefit to customer vs. to corporation for information systems), which is further grounded in the problem context, as the authors described above. As a result, the authors used a pie chart within the circle representing the value to depict the distribution between firm and customer. For other settings, theoretically, additional participants or parties can also be added. This configuration helps businesses to identify the potential need to provide incentives for users in cases where the vast majority of benefit would accrue at the firm. Without this understanding, adoption and uptake could be very limited, given that the majority of people are driven by personal utility maximization. In this context, in order to optimize the overall objective function, an incentive compatible mechanism is needed to align the principal’s objective function with the agent’s objective function (Holmstrom & Milgrom, 1991; Hurwicz, 1973; Jensen & Meckling, 1976). Incentives are provided for the agent, so that, while the agent fulfills her/his objective function, she/he also fulfills the principal’s objective function, leading to a win-win situation between the principal and the agent. Coming up with such an incentive compatible mechanism is a dynamic and ever evolving process that can be continuously improved after initial set-up, based on accrued data.

**DEMONSTRATION OF EMOTION DETECTION APPLICATION VALUE APPROACH**

The authors used their framework to explore and categorize applications for emotion detection and to validate the proposed approach. In order to understand the potential value of detecting emotions, one could first draw on relevant research about one of the most primitive—yet heavily implemented—business applications of emotion detection: User self-reported emotions. Today, customers are inundated with online satisfaction surveys such as net promoter score indices (Baehre et al., 2022), touchscreens deployed during airline check or in toilets, and online rating systems. Most of these require a simple indication of emotion or satisfaction resulting from experiencing a service or product, using for example smiley faces and/or color-based Likert scales. However, there are several problems related to self-reported emotions, which limits the applicability and usefulness of this approach. It tends to be intrusive, inconvenient, and sometimes time-consuming for customers, resulting in low participation numbers. Often, only very happy or dissatisfied customers report their feelings, thus increasing the problem of self-selection bias, making the results heavily unreliable and thus of limited usefulness for the main application of service improvement.

Beyond getting ideas from prior technologies as the authors described above, in order to derive additional emotion detection applications for framework validation, they tasked students with finding ideas for using the detection of human emotions to start a new business or to create strategic advantage for an existing business. The researchers drew participants predominantly from MBA courses on digital business and information systems; thus, these participants were equipped with relevant knowledge about business and technology issues and their interplay. Participants also generally hold several years of practical experience in different industries. The researcher provided some preliminary information on the technology to the students in the form of newspaper articles. The main task set for the students was to “come up with an idea (other than the ones mentioned in the documents) to use the detection
of human emotions to create strategic advantage.” The authors followed the same procedure in data collection in two different countries (i.e., U.S. and Turkey) at leading business schools as part of a take-home exam. They chose two countries from different regions to reduce cultural bias. In total, 67 teams of two students each (25 teams from the U.S. and 42 teams from Turkey) participated. The authors sorted and categorized the resulting ideas according to their framework, and eliminated duplicates. At the end, 32 unique application ideas remained. The vast majority related to service industries, primarily health care, education, entertainment, and security. In addition, several use cases related to human resources, suggesting cross-industry potential, as well as some examples from politics, smart homes or photo sharing. Using these data, the proposed framework is used to represent the main applications for the service industry, abstracting from differences between more specific industries for the sake of brevity (Figure 1). Therefore, this result acts as a first demonstration of the applicability of the proposed framework.

Thus, the authors found that, when the value framework is applied to the case of emotion detection capabilities, it is possible to clearly depict and differentiate between application ideas. Figure 1 clearly shows an uneven value distribution between firm and user. In conjunction with challenges in adoption as the authors detailed, this probably indicates that mitigating measures need to be implemented to assure uptake and value generation. This underlines that the framework is helpful in the further analysis, and itself provides support and value to decision-makers. With privacy concerns of end users as one of the biggest problems associated with emotion detection, privacy preserving measures are of utmost importance. Providing customers with information about the presence of such technology and how the captured emotion data will be used are vital points to maintain perceptions of trust. It is necessary to demonstrate that the technology is deployed in a way that is fit-for-purpose. Clearly
eliciting customer consent, especially choosing an opt-in rather than opt-out mechanism, is perhaps a more effective way to mitigate concerns. However, this probably entails the increased risk of limited uptake and self-selection bias. An important role falls on government, particularly regulatory authorities, to enact laws and regulations to preserve privacy of sensitive information, while also enabling appropriate business use.

As the expertise on customer emotions and their use will be small in the beginning, continuous improvement and learning on judging, deciding, and implementing are necessary through collecting a large number of data and incidents. Initial customers might need to be subsidized until a critical mass is reached. After that stage, positive externalities will enhance the benefits and added value, which will grow exponentially. At the same time, negative externalities such as hacker attacks and wrongful use of emotion data might appear. After some time, this could lead to a customizable, individually-adaptable, and precision marketing service that would facilitate dynamically-adjusted prices at the individual level. This would enable companies to extract almost full consumer surplus, while offering exactly what people want. At this stage, the service is incentive-compatible, since users get what they want and companies charge accordingly, leading to a win-win situation and direct benefits to both parties. This situation also leads to indirect benefits through increased profits of companies, which allows the development of more services, which, in turn, could increase customer satisfaction and expenditures. Usage-based pricing might be another alternative.

One possible solution is market mechanisms that allow monetizing emotion for customers (e.g., through micro-payments). This also provides an incentive compatible mechanism ensuring sufficient participation. In this context, an important business model could be to create third party institutions or platforms (Bakos & Katsamakas, 2008; Gawer & Cusumano, 2014) for capturing, storing, and monetizing emotion data. These arms-length providers could accumulate higher trust as compared to individual companies, while still allowing a large amount of value to be generated by them, especially in nonpersonalized contexts. They would connect the two sides, customers and companies, allowing externalities and network effects as the authors laid out above.

CONCLUSION

In this paper, the authors presented a new value framework for the evaluation of applications of emerging technologies by organizations, based on design science research grounded in problems of adoption and business use of emotion detection technology. As a main distinguishing feature to prior approaches and research, the authors’ framework allows to analyze and show value generation, but also capture and distribution of value between players. The authors validated the framework for the use context of emotion detection based on data they collected from MBA students, with a first evaluation showing that it indeed can capture related business ideas. As the findings showed, the framework can help organizations to find and select appropriate adoption areas and can be used as a starting point for risk and problem mitigation, thus aiding in successful adoption and business value generation. This underlines both a contribution to research on business value of IT, respectively digital transformation and its analysis, as well as the relevance for business decision-makers when they are faced with new technologies and tasked to select or prioritize respective applications. Managers can use this framework as a tool for analysis in situations where new technologies are available, and they have to determine appropriate investments into applications within their organization. Based on this analysis, in the foreseeable future, emotion detection could become a commodity, over time. The important issue is to convert the generated information into strategic uses. There may also be a platform matching users to emotions and interpreting them, as well as potential emotion data sharing among organizations (Elsaify & Hasan, 2021). Future work would entail to validate the value framework for other technologies and contexts with potential changes and refinements.

Like most research, this paper is also subject to limitations. One limitation is the fact that the authors demonstrated the proposed framework in use so far for one particular context, namely the
technology of emotion detection. The authors’ choice was on the basis of using application ideas derived from student projects. Although they took care that the students had sufficient background as well as industry experience, further validation within corporate settings would be a promising step for future research. Similarly, a validation through top-level management regarding the value derived from employing the new framework would provide important further insights and potential ways of improvement. Lastly, applying the framework to a range of additional settings and technologies would be an important next step.

ACKNOWLEDGMENT

The authors of this publication declare there is no conflict of interest.

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.
REFERENCES

Baehre, S., O’Dwyer, M., O’Malley, L., & Lee, N. (2022). The use of Net Promoter Score (NPS) to predict sales growth: Insights from an empirical investigation. *Journal of the Academy of Marketing Science, 50*(1), 67–84. doi:10.1007/s11747-021-00790-2

Bakos, Y., & Katsamakas, E. (2008). Design and ownership of two-sided networks: Implications for Internet platforms. *Journal of Management Information Systems, 25*(2), 171–202. doi:10.2753/MIS0742-122250208

Bartlett, M. S., Hager, J. C., Ekman, P., & Sejnowski, T. J. (1999). Measuring facial expressions by computer image analysis. *Psychophysiology, 36*(2), 253–263. doi:10.1017/S004857729971664 PMID:10194972

Basu, S., Jana, N., Bag, A., Mahadevappa, M., Mukherjee, J., Kumar, S., & Guha, R. (2015). Emotion recognition based on physiological signals using valence-arousal model. In 2015 *Third International Conference on Image Information Processing (ICIIP)* (pp. 50-55). IEEE. doi:10.1109/ICIIP.2015.7414739

Bergeron, F., Buteau, C., & Raymond, L. (1991). Identification of strategic information systems opportunities: Applying and comparing two methodologies. *Management Information Systems Quarterly, 15*(1), 89–103. doi:10.2307/249439

Brown, L. S. (2017). The influence of music on facial emotion recognition in children with autism spectrum disorder and neurotypical children. *Journal of Music Therapy, 54*(1), 55–79. PMID:28040801

Cebula, K. R., Wishart, J. G., Willis, D. S., & Pitcairn, T. K. (2017). Emotion recognition in children with Down syndrome: Influence of emotion label and expression intensity. *American Journal on Intellectual and Developmental Disabilities, 122*(2), 138–155. doi:10.1352/1944-7558-122.2.138 PMID:28257244

Chen, M., Yang, J., Zhu, X., Wang, X., Liu, M., & Song, J. (2017). Smart home 2.0: Innovative smart home system powered by botanical IoT and emotion detection. *Mobile Networks and Applications, 22*(6), 1159–1169. doi:10.1007/s11036-017-0866-1

Chen, Y. L., Chang, C. L., & Yeh, C. S. (2017). Emotion classification of YouTube videos. *Decision Support Systems, 101*, 40–50. doi:10.1016/j.dss.2017.05.014

Dagar, D., Hudait, A., Tripathy, H. K., & Das, M. N. (2016). Automatic emotion detection model from facial expression. In *Proceedings of the 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCT)* (pp. 77-85). IEEE. doi:10.1109/ICACCT.2016.7831605

Dwoskin, E., & Rusli, E. M. (2015). The technology that unmasks your hidden emotions. *The Wall Street Journal, 265*(23), B1-B8.

Ekman, P. (1984). Expression and the nature of emotion. In K. Scherer & P. Ekman (Eds.), *Approaches to emotion* (pp. 319–344). Erlbaum.

Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion, 6*(3-4), 169–200. doi:10.1080/02699939208411068

Ekman, P., Sorenson, E. R., & Friesen, W. V. (1969). Pan-cultural elements in facial displays of emotion. *Science, 164*(3875), 86–88. doi:10.1126/science.164.3875.86 PMID:5773719

Elsaify, M., & Hasan, S. (2021). Data exchanges among firms. *Digital Business, 1*(2), 100010. doi:10.1016/j.digbus.2021.100010

Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2014). Embracing digital technology: A new strategic imperative. *MIT Sloan Management Review, 55*(2), 1.

Gawer, A., & Cusumano, M. A. (2014). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management, 31*(3), 417–433. doi:10.1111/jpim.12105

Ghosh, S., Hiware, K., Ganguly, N., Mitra, B., & De, P. (2019). Emotion detection from touch interactions during text entry on smartphones. *International Journal of Human-Computer Studies, 130*, 47–57. doi:10.1016/j.ijhcs.2019.04.005

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *Management Information Systems Quarterly, 37*(2), 337–355. doi:10.25300/MISQ/2013/37.2.01
Hevner, A., March, S. T., Park, J., & Ram, S. (2004). Design science research in information systems. *Management Information Systems Quarterly, 28*(1), 75–105. doi:10.2307/25148625

Hevner, A. R. (2007). A three cycle view of design science research. *Scandinavian Journal of Information Systems, 19*(2), 4.

Holmstrom, B., & Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law Economics and Organization, 7*(special_issue), 24–52. doi:10.1093/jleo/7. special_issue.24

Horbacher, A., & Hess, T. (2016). What does a Chief Digital Officer do? Managerial tasks and roles of a new C-level position in the context of digital transformation. In *Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 5126-5135). IEEE. doi:10.1109/HICSS.2016.634

Hurwicz, L. (1973). The design of mechanisms for resource allocation. *The American Economic Review, 63*(2), 1–30.

Ives, B., & Learmonth, G. P. (1984). The information system as a competitive weapon. *Communications of the ACM, 27*(12), 1193–1201. doi:10.1145/2135.2137

Jeffery, M., & Leliveld, I. (2004). Best practices in IT portfolio management. *MIT Sloan Management Review, 45*(3), 41–49.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics, 3*(4), 305–360. doi:10.1016/0304-405X(76)90026-X

Kohli, R., & Grover, V. (2008). Business value of IT: An essay on expanding research directions to keep up with the times. *Journal of the Association for Information Systems, 9*(1), 23–39. doi:10.17705/1jais.00147

Lee, W., Xiong, L., & Hu, C. (2012). The effect of Facebook users' arousal and valence on intention to go to the festival: Applying an extension of the technology acceptance model. *International Journal of Hospitality Management, 31*(3), 819–827. doi:10.1016/j.ijhm.2011.09.018

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & Information Systems Engineering, 57*(5), 339–343. doi:10.1007/s12599-015-0401-5

McAfee, A., & Brynjolfsson, E. (2008). Investing in the IT that makes a competitive difference. *Harvard Business Review, 86*(7/8), 98–107.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *Management Information Systems Quarterly, 28*(2), 283–322. doi:10.2307/25148636

Muehlburger, M., Kannengiesser, U., Krumay, B., & Stary, C. (2020). A framework for recognizing digital transformation opportunities. In *Proceedings of the 28th European Conference on Information Systems (ECIS)*. AIS.

Mukhopadhyay, M., Pal, S., Nayyar, A., Pramanik, P. K. D., Dasgupta, N., & Choudhury, P. (2020). Facial emotion detection to assess Learner’s State of mind in an online learning system. In *Proceedings of the 2020 5th International Conference on Intelligent Information Technology* (pp. 107-115). ACM. doi:10.1145/3385209.3385231

Nan, N., & Tanriverdi, H. (2017). Unifying the role of IT in hyperturbulence and competitive advantage via a multilevel perspective of IS strategy. *Management Information Systems Quarterly, 41*(3), 937–958. doi:10.25300/MISQ/2017/41.3.12

Notowidigdo, M. H. (1984). Information systems: Weapons to gain the competitive edge. *Financial Executive, 52*(2), 20–25.

Parker, M. M., & Benson, R. J. (1988). *Information economics: Linking business performance to information technology*. Prentice-Hall.

Peffers, K., & Gengler, C. E. (2003). How to identify new high-payoff information systems for the organization. *Communications of the ACM, 46*(1), 83–88. doi:10.1145/602421.602424
Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems, 24*(3), 45–77. doi:10.2753/MIS0742-1222240302

Picard, R. W. (1997). *Affective computing*. MIT Press.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. FreePress.

Renkema, T. J., & Berghout, E. W. (1997). Methodologies for information systems investment evaluation at the proposal stage: A comparative review. *Information and Software Technology, 39*(1), 1–13. doi:10.1016/0950-5849(96)85006-3

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *Management Information Systems Quarterly, 27*(2), 237–263. doi:10.2307/30036530

Sharma, A. N., Barron, E., Le Couteur, J., Close, A., Rushton, S., Grunze, H., Kelly, T., Ferrier, I. N., & Le Couteur, A. S. (2017). Facial emotion labeling in unaffected offspring of adults with bipolar I disorder. *Journal of Affective Disorders, 208*, 198–204. doi:10.1016/j.jad.2016.10.006 PMID:27792963

Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *The American Economic Review, 49*(3), 253–283.

Soleymani, M., Asghari-Esfeden, S., Fu, Y., & Pantic, M. (2016). Analysis of EEG signals and facial expressions for continuous emotion detection. *IEEE Transactions on Affective Computing, 7*(1), 17–28. doi:10.1109/TAFFC.2015.2436926

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making, 12*(3), 183–206. doi:10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO;2-F

Tjan, A. K. (2001). Finally, a way to put your Internet portfolio in order. *Harvard Business Review, 79*(2), 76–85. PMID:11213700

Turner, P. (2008). Being-with: A study of familiarity. *Interacting with Computers, 20*(4-5), 447–454. doi:10.1016/j.intcom.2008.04.002

Urbach, N., Ahlemann, F., Böhmann, T., Drews, P., Brenner, W., Schaudel, F., & Schütte, R. (2019). The impact of digitalization on the IT department. *Business & Information Systems Engineering, 61*(1), 123–131. doi:10.1007/s12599-018-0570-0

Zhang, Z., Cui, L., Liu, X., & Zhu, T. (2016). Emotion detection using Kinect 3D facial points. In *Proceedings of the International Conference on Web Intelligence (WI), 2016 IEEE/WIC/ACM* (pp. 407–410). IEEE.
Stefan Koch is Professor and Chair at Johannes Kepler University Linz, Department of Business Informatics – Information Engineering. He received his Ph.D. from WU – Vienna University of Economics and Business. His current research interests include user and open innovation, the open source development model, the management and governance of information systems, ERP systems, and software business. He has published over 30 papers in peer-reviewed journals, including Information Systems Journal, Information Economics and Policy, Decision Support Systems, Empirical Software Engineering, Information and Software Technology, Electronic Markets, Information Systems Management, Journal of Database Management, Journal of Software Maintenance and Evolution, Enterprise Information Systems, Journal of Services Marketing, Journal of Global Information Technology Management, International Journal of Human Resource Management and Wirtschaftsinformatik, and over 30 in international conference proceedings and book collections.

Kemal Altinkemer is a professor of management at Purdue University, Krannert School of Management where he has worked for 35 years. He is in Management Information Systems (MIS) area, where he serves as area coordinator. He has published more than 50 journal articles, and he has more than 50 conference proceedings. He serves as associate editor in five journals.