

Perspective

Digitalization in psychology: A bit of challenge and a byte of success

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THE BIGGER PICTURE Digitalization affects research in almost every scientific discipline. This becomes apparent in new approaches of data analysis and management, such as machine learning, but also in new therapeutic approaches using digital and virtual technologies in patient care. Thus, digitalization can be considered a promising area in the field of evidence-based health care. However, a glance at the history of such applications reveals that the interaction between psychology and digital technologies has a long tradition. This perspective gives a brief overview on how digital technologies have emerged into psychological science in the past and what future challenges and opportunities are.

SUMMARY

Digital transformation affects research in almost every scientific discipline. We give a brief overview on how digital technologies have emerged into psychological science in the past and what the challenges and opportunities currently are. Providing two recent examples from our own research, we argue that interdisciplinary collaborations that make use of digital approaches without giving up a strong theoretical foundation will greatly enhance psychological research in the future.

A LONG HISTORY OF SUCCESS

One of the main principles of every scientific discipline is to find and to explain patterns in the subject of their research—for example, in the case of spatial coat textures in animals,¹ in cosmic-ray arrival directions,² or in spatial movements in a gardening task to detect mental burden.³ In these examples of research, all published very recently, the authors make use of advanced computational methods in the context of, for instance, image processing, neural networks, or digital movement analysis. These approaches, that all build on recent advances in computational power and algorithm development, are one of the latest examples of how digitalization is shaping our scientific discipline.

Digital approaches as such, however, are not at all new to psychological science. Already in the very first era of digitalization, psychologists made use of punch cards for psychological interpretations of the Rorschach test when analyzing the perceptions of inkblots⁵ or later using mainframe computers, such as the IBM 650, in determining the factor analytic structure of the House-Tree-Person-Test.⁶ Also, concepts such as predictive modeling or artificial intelligence studies are not at all new in psychological science.^{7,8}

According to a review conducted during the time of mainframe computers, more than three-quarters of psychology departments (76.1%) in the United States are reported to have a com-

puter installed at their department.⁹ In parallel, the first major digital computer labs for cognitive psychology were developed (Figure 1 including, for example, automated eye tracking systems used for high-quality psychological research.⁴

With the turn from mainframe computers to microcomputers, the application of digitalization continued. Examples include the development of a virtual sand box to detect mental disorders from virtually created landscapes¹⁰ or the use of avatars to assess behavioral patterns of patients suffering from schizophrenia.¹¹ These two examples are just a tiny selection of all digital solutions used in psychological research. More systematically, one can distinguish between devices used for data collection (allowing paradigms, such as real-time experience sampling¹² or the collection of behavioral parameters otherwise not accessible to direct observation¹³), algorithms used for data analysis (such as models predicting personality from social network data¹⁴ or fine motor development scores from videos of children's movements¹⁵), and more interactive applications in which machines interact with humans for research or collaborative purposes^{16–18}). In summary, digitization in psychological science is not at all a new topic and has been around for more than six decades, very often on the cutting edge of research methodology.¹⁹

PROMISES OF INTERDISCIPLINARY COOPERATION

More than 60 years ago, Wrigley pointed out that “electronic computers will bring psychologists into greater contact with



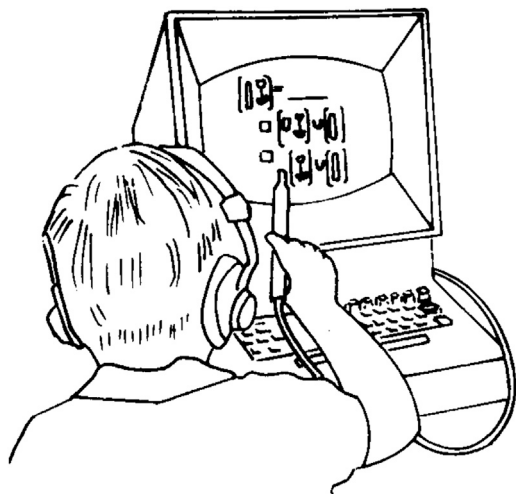


Figure 1. Schematic drawing of a pupil solving a psychological task on a computer in the 1970s
Adopted from Aaronsen et al.⁴

physicists and applied mathematicians.”²⁰ This is still true today, although we would probably expand this circle to include disciplines that did not exist at the time. With growing complexity of the digital systems and modern algorithms, the need for specialization has dramatically increased, and so has the need to talk across disciplinary boundaries.

As with all interdisciplinary endeavors, this will be challenging.^{21,22} Still, we want to argue that to make use of the new possibilities that digitalization brings about, interdisciplinary collaboration is crucial. Due to the complexity of the systems and algorithms, psychological researchers alone will not be able to set up certain paradigms or run certain algorithms. However, when joining forces with technicians, engineers, data scientists, or applied mathematicians, new approaches to studying behavior and analyzing behavioral data will become available. Two examples from our own research should illustrate this.

In a recent study, we wanted to evaluate the power of a digital tree-drawing task for the prediction of early signs of dementia.²³ A multidisciplinary team, including computer scientists, psychologists, and art therapists, developed this test. Patients were asked to paint a tree from memory, using a digitizing tablet with a pressure-sensitive pen and an underlying drawing software that supported the calculation and the analysis of the drawing style [Figure 2](#).

The parameters collected by the software were, for example, concerning the amount of space used for the drawing, the interruption of drawing lines, drawing speed, line width, or the use of colors. Our main aim was to show that certain drawing characteristics could be used to determine the degree of cognitive impairment. In addition to a diagnostic tool for the early identification of cognitively impaired persons, our team expected that this innovative procedure would lead to a minimally stigmatizing test, which in turn would increase the motivation to participate in dementia screening. Due to this interdisciplinary approach, which included different perspectives and theories from psychology and art therapy, and due to an early and continuous involvement of computer scientists who implemented these

ideas, we found that, compared with healthy subjects, patients with cognitive impairment used less colors, narrower line widths, and paused more often. They also had a lower painting velocity and their pictures had less contrast, image size, and complexity. This insight linking drawing characteristics and cognitive impairment would hardly have been possible without this interdisciplinary collaboration and the technology on which this collaboration was based.

The same conclusion can be made with regard to our second example. With the help of graphic art technicians, we have developed a perfect virtual copy of our lab [Figure 3](#). When putting on the virtual head set, participants felt as they would be exactly in the same room that they have been before.

The only difference to reality was the avatar they were embodying, because we randomly assigned young participants to either an age-congruent (i.e., young) or an age-incongruent (i.e., old) avatar ([Video S1](#))

We were expecting—and actually found—that embodying an older avatar would activate (predominantly negative) age stereotypes that in turn would deteriorate participant performance on both a physical and a memory task.²⁴ Furthermore, using machine learning algorithms to predict the movement patterns of the participants, we found that the experimental and the control groups differed in the way they were moving their arms.²⁵ More specifically, we have been using and comparing different classification techniques (e.g., support vector machines, random forest, or convolutional neural networks) to predict group membership (i.e., age-incongruent experimental group and age-congruent control group). The difference in movement patterns was so strong that we could almost perfectly classify participants based on a short and randomly drawn movement sample of just a few seconds. Yet, it was so subtle that we could not detect it at all using more traditional data analytic approaches. Without the use of virtual reality technology and without the help of technicians and digital designers, paradigms such as the one just described, would simply not be possible or at least not feasible. Moreover, without the help of data scientists from applied mathematics, we would have missed important effects of negative self-stereotyping with potentially devastating long-term consequences for health and well-being.

Taken together, our examples demonstrate that making use of digital systems and modern algorithms allows obtaining new insights that can be relevant from both a theoretical and an applied perspective. Digitalization provides a new toolbox for psychological research that, however, often can only be used with the assistance of specialists that know how to handle these tools.

THERE IS NOTHING MORE PRACTICAL ...

The decisive factor for the success of such interdisciplinary collaboration is (and always has been) that it is built on a sound theoretical basis. Just because research is digital, or involves machine learning, or any other fancy technology or algorithm, does not automatically make it good research. Interdisciplinary collaboration, in particular such that covers very much unrelated disciplines, requires that no compromise is made on the theory underlying a research question. We may find new ways to operationalize our constructs, identify new indicators of a latent

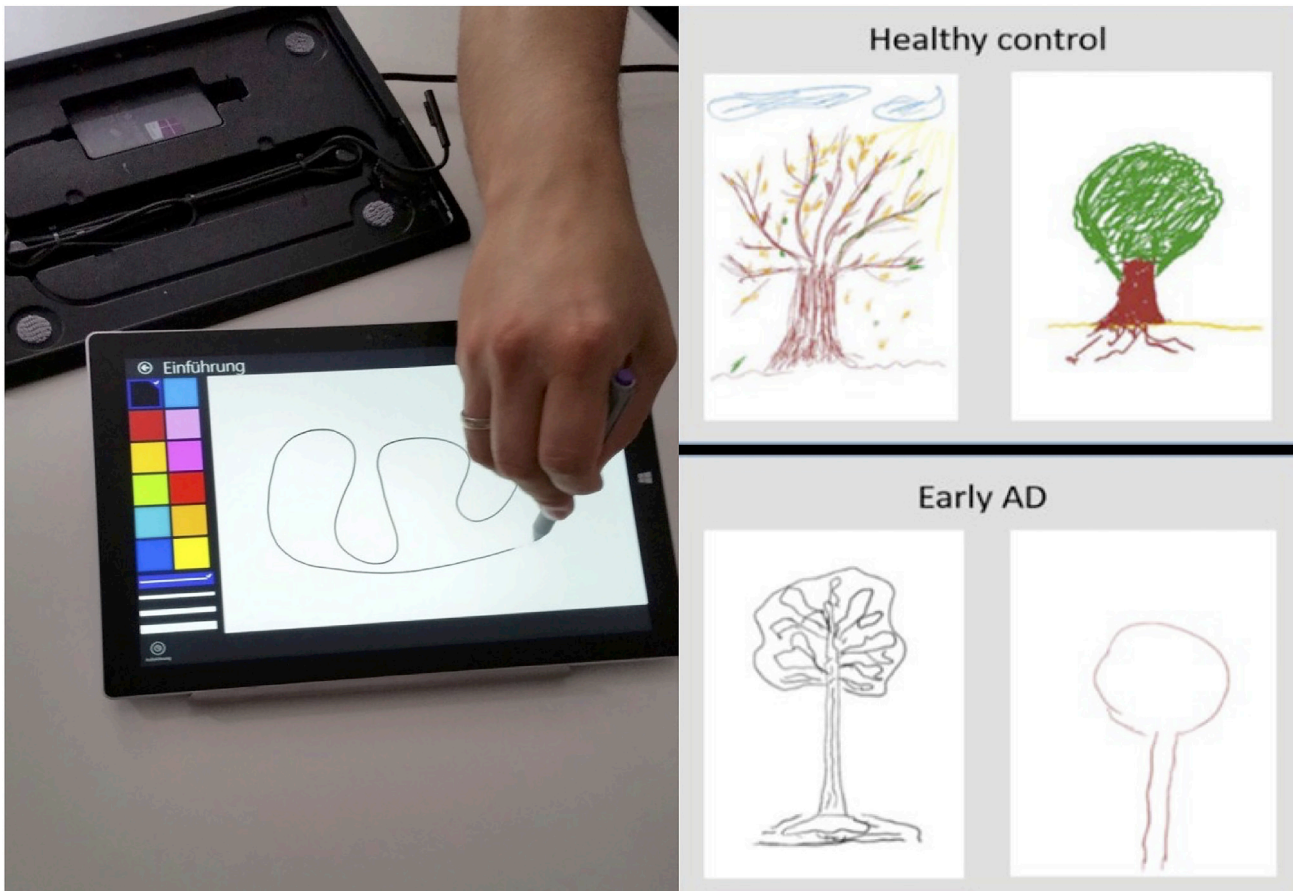


Figure 2. The digital tree drawing test

behavioral dimension, or find new ways to analyze our data. These all are ways in which interdisciplinary collaboration may lead to new insights that each discipline working for itself could not have obtained alone. However, “creativity” in operationalization should be accompanied by “conservatism” in its theoretical foundation, otherwise research could become arbitrary and at the end not useful for anybody. This is nicely demonstrated by a recent study that investigated the involvement of mental healthcare professionals in the design of anxiety apps.²⁶ They not only found that, in almost half of the apps, no mental health professionals were involved but also that those apps with professional involvement had their download and installation number increased by five times.

CHALLENGES IN SIGHT

Today, psychology, like every scientific discipline in life science and health care, is confronted with the rapid development of digitalization. The chance is not only to adopt psychological experiments into the new digital framing, but also to create “a new social context with such unique characteristics that it gives an opportunity for testing existing theories and concepts of psychology, in order to identify new variables or introduce new mediating factors.”²⁷ Digitization in psychological science

also opens up new opportunities for international collaboration projects. Complex multi-lab projects involving scientists from many different countries would be impossible without a comprehensive digital approach. Initiatives such as the *Open Science Collaboration* or the *Psychological Science Accelerator* have been rightfully praised for pointing the way toward a more inclusive, reliable, and generalizable psychological science.^{28,29}

Nevertheless, there are still many challenges that must be overcome. One of the most important ones—but at the same time one that may be easily overlooked—is the challenge of construct validity. When confronted with a “fancy” technological solution promising to measure some latent construct, there are some risks that might jeopardize the appropriateness of inferences based on the observations made. For instance, research on the so-called mode effects in educational measurement shows that apparently the scores of the very same assessment differ depending on whether that assessment was conducted in paper-and-pencil mode or on a computer.³⁰ Depending on the experimental paradigm, we might be assessing more-or-less construct-irrelevant variance, which might become particularly problematic if this variance is correlated with the construct that we are actually interested in (e.g., computer literacy and general intelligence assessed with the help of a computer). In

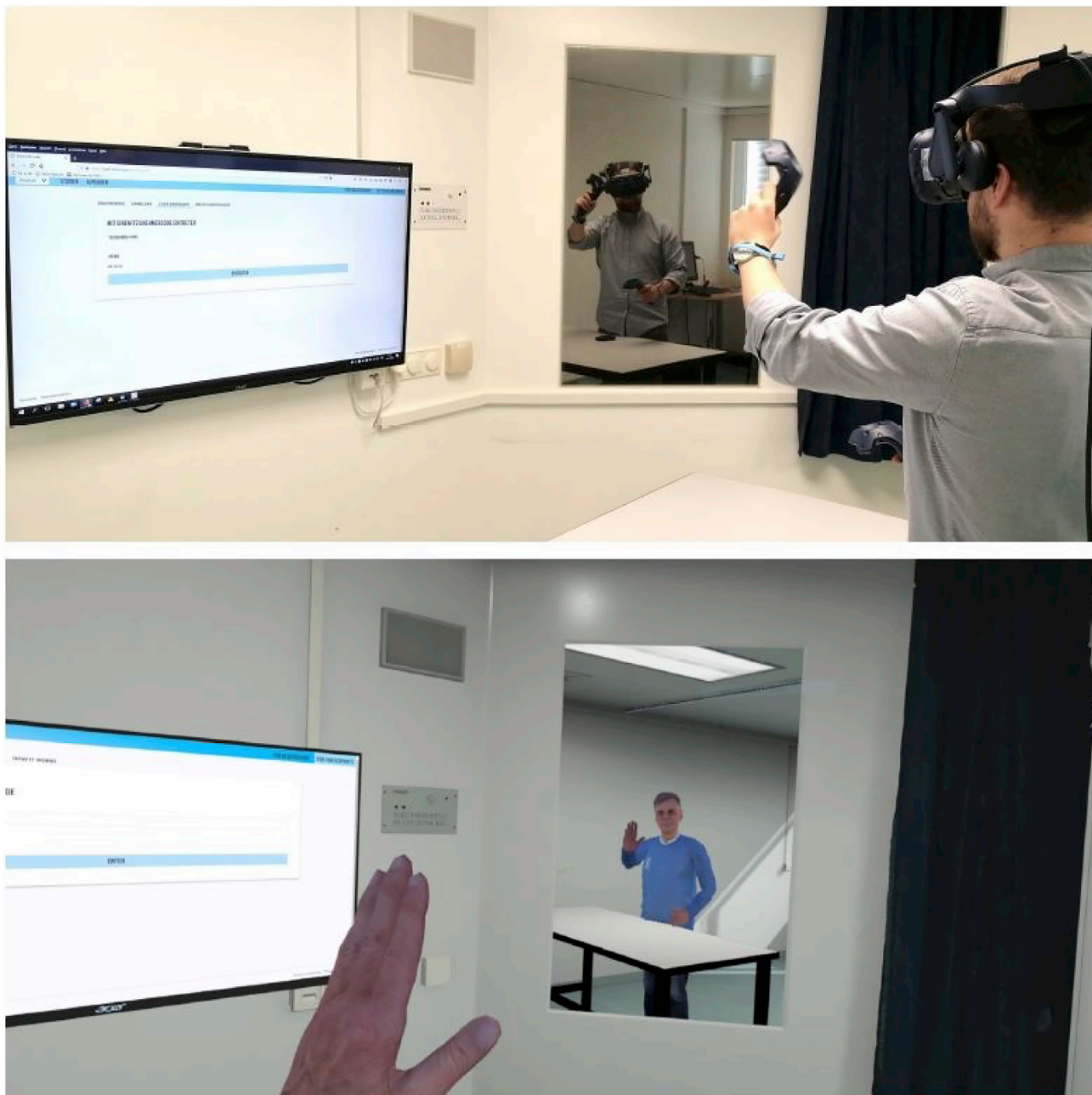


Figure 3. Setup for investigating aging stereotypes in virtual reality

any case, the more complex a derived score becomes, the less clear its meaning might become and comparability with previous studies might be restricted.

Another relevant challenge worth mentioning specifically relates to the interpretability of advances in statistical models, such as random forest or neural network approaches. When used for prediction, such models often result in high to very high accuracy, making them attractive for a broad range of applications.^{31–33} However, such models are of little help when researchers aim at explaining patterns of behavior. Although there are efforts for making artificial intelligence explainable (xAI),^{34,35}

we have to accept that there will always be “black boxes” that are not at all suited for explanation and subsequent theory building. On the one hand, this might become a serious limitation for applying such models in psychological science. On the other hand, however, there are researchers arguing that psychological science might even profit very much from an increased focus on prediction rather than explanation.³⁶

Furthermore, not every psychological study can be digitized equally well. In particular, studies that require direct interaction between two or more people are sometimes difficult to transfer to the digital realm. Moreover, international collaboration

projects often bring together participants from various countries, which requires careful translation of materials, both in terms of linguistic similarity and cultural differences.^{37,38} This, however, is not necessarily done in very conscious ways, especially when the researcher's main motivation is to save participant reimbursement money by conducting experiments online with participants from low-income countries without very much cultural sensitivity.³⁹

Still, however, most of the participants in psychological experiments come from Western, educated, industrialized, rich, and democratic (i.e., WEIRD) societies.⁴⁰ While digitization in principle holds the promise of transferring psychological expertise to more geographically remote regions, this transfer can of course only succeed if the necessary infrastructure, training, and skills to conduct the studies are already available. Other potential challenges include that digital labs blur the distinction between work and home life,^{41,42} and that—at least for some researchers—the primary motivation for conducting digital research seems to be convenience rather than which method is best suited to answer the research question.⁴³ If, however, digitization is merely used to answer old questions with new methods, then this rarely leads to real scientific progress.^{44,45}

WALKING THE EXTRA MILE TOGETHER

After giving some examples of successful interdisciplinary collaborations, the question remains how data scientists can meet and engage with experimental psychologist in a practical way. The examples given have pointed to both the realm of data collection and the realm of data analysis. This is by no means a coincidence, since data are the common denominator of the two disciplines. Naturally, data will be the common interest of both. In our experience, psychological researchers are often looking for innovative ways of collecting data and/or analyzing them with methods that go beyond their traditional toolbox. Access to technological expertise and state-of-the-art statistical modeling is what motivates them to seek a collaboration. Data scientists, in turn, are often keen to see their devices and algorithms applied in a real world setting to answer a relevant research question. Access to participants and the opportunity to put their methods to a test against the backdrop of a complex research question is what drives their motivation to collaborate. These two complementary interests of psychological and data scientists could be brought together in the emerging field of psychological data science. Such a “merging of psychology and data science” might enable researchers to be “well-positioned in their ability to incorporate data science into their work to advance and promote our understanding of key factors associated with important psychological outcomes.”⁴⁶

In particular, this idea might already be included in undergraduate and postgraduate education, hence creating a space in which students and researchers from data science with their specialized knowledge would be able to meet their psychological counterpart to solve practical problems in collaborative teams.⁴⁷ This type of problem-oriented learning at least for us seems as the most promising didactic approach to bridge the different disciplines without overburdening the already

dense curricula with too many introductory lectures. In the best case, this would help to raise a new generation of bilingual researchers that are fluent in both disciplines—with potentially very positive repercussions for the careers of these researchers. Against this backdrop, it is not at all surprising that, for instance, the University of Wisconsin data science program heavily advertises that “combining psychology, research methods and statistics can lead to a powerful data science career.”⁴⁸

CONCLUSION

Our main argument was that, throughout the history of psychological science until today, psychology has been open to the promises of (digital) technology and has very much profited from interdisciplinary collaboration with engineers, technicians, applied mathematicians, and many others. As any other interdisciplinary collaboration, this type of collaboration has its challenges. A poorly designed psychological study does not improve one bit just because it uses a digital approach. However, with a strong theory in mind and some sensitivity to the challenges that digitalization at large brings to our discipline and to society as a whole, we are well equipped for harvesting the fruits of the new technologies around us.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.patter.2021.100334>.

AUTHOR CONTRIBUTIONS

Conceptualization, T.O. and M.J.T.; writing – original draft, T.O., J.P.R., and M.J.T.; writing – review & editing, T.O., J.P.R., and M.J.T.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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