

Serious Gaming for Behavior Change: The State of Play

Serious gaming guides targeted behavior change to improve behaviors in everyday living. This survey of the field focuses on two case studies—one game aims to improve the social behavior of autistic children, and the other helps migrants interact with locals.

Serious gaming is often described as the use of digital gaming technology to address a specific set of learning objectives or behavioral goals. Such games seek to build on the increasingly pervasive role games play as an entertainment medium, providing an engaging and entertaining way of communicating educational content along with efficient behavior analysis. As Richard Lingard once said, “If you would read a man’s Disposition, see him Game; you will then learn more of him in one hour, than in seven Years [of] Conversation.”¹

In this sense, serious games hold great promise for behavior analysis of human players. Moreover, they can encourage positive behavior change in a playful and pleasant way—something games have sought to achieve in a variety of ways. Common is the central role the game plays as either a medium for conveying educational messages or for encouraging certain activities through game-based elements, such as competition or rewards. However, a significant challenge has been getting the players to apply the changed behavior in the real world. Pervasive computing can help overcome this gap, letting players at times learn

the behavior in the environment in which it must be applied.

Furthermore, although serious games show great application potential for individuals on the autistic spectrum or for other target groups that experience difficulties in human-to-human communication, current games for behavior change rarely address human-to-human interaction. This would require a holistic approach that takes into account behavioral cues from multisensory input—possibly including speech, video (facial expressions and gestures), and physiological sensors.

In this light, we first examine the state of play in serious games, focusing on *affective analysis*—that is, the recognition and analysis of players’ emotions. We then present two exemplary case studies from the context of teaching appropriate behavior in human-to-human interaction and consider how to exploit mobile computing for automatic, multimodal analysis of human behavior.

Behavior Analysis and Feedback

Here, we explore how knowledge transfer, gamification, and social learning can help induce behavioral change. Two unique traits of games make them particularly interesting as tools for analyzing and changing player behaviors. The first is their universal appeal and ability to reach certain demographics traditionally resistant to other forms of direct messaging or intervention, such as adolescents. The second

Björn W. Schuller
Joanneum Research
Forschungsgesellschaft mbH

Ian Dunwell
Coventry University

Felix Weninger
Technische Universität München

Lucas Paletta
Joanneum Research
Forschungsgesellschaft mbH

is their ability to capture and retain a user's attention for a significant time period. Consider, for example, the average 90-minute use of the online serious game *Code of Everand*, which has 100,000 players, compared to the three-minute visit duration shown for many static websites.²

Yet knowing how to fully use this contact time to achieve a behavioral outcome without compromising the “fun” of the game remains a demanding task—in particular, because behavioral outcomes can prove difficult to measure. Self-reported planned behavior often deviates from observed behavior,³ and observing large samples over an extended period of time is seldom practical. However, it might be possible to glean some insight regarding the behavioral impact of a serious game by analyzing the player's interactions in the game itself. The notion of video games as research instruments is well established,⁴ yet how to understand the unique data that can be captured through play remains a central research topic.

Players might adopt an “intuitive” approach to play, whereby they willfully explore wrong choices and worst cases as well as correct actions, so understanding their level of knowledge or attitude is likely not as simple as equating this to the “correctness” of their in-game actions.⁵ Indeed, a behaviorist paradigm, in which a game attempts to replicate intended behaviors in a virtual or gaming context, has been argued as ineffective in many cases, because players seek to defeat the game by circumventing rather than attaining its intended behavioral outcomes.⁶ It's thus important to explore how large-scale capture of data from players might be ethically achieved and used to more effectively identify behavioral and attitudinal trends. Subsequently, games might be adapted either to individual users⁷ or in response to findings of large-scale user studies.

Several models have been employed in serious games seeking to invoke a change in the players' behaviors.

Knowledge Transfer

The first model is based on knowledge transfer—that is, conveying educational content to learners to better inform their decision making based on knowledge of the consequences of a certain behavior. This can be particularly effective with younger audiences.

In a randomized control trial, researchers observed a positive behavioral outcome in young cancer patients who played the game *Re-Mission*, compared to an entertainment game serving as a placebo.⁸ In this case, the game sought to educate players about the nature of their cancer and its treatment to help them adhere to treatment programs with short-term negative side effects but long-term benefits. Thus, the behavioral model underpinning this game was one of information transfer, exploiting the engaging and entertaining medium of the game to appeal to a young audience that might be more resistant to less immersive materials.

A similar route has been taken with games tackling childhood obesity,⁹ which encourage exercise through gaming by integrating emerging gaming hardware for an active user experience.¹⁰ Although the benefits in terms of energy expenditure might

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countries, such as the UK, the problem doesn't stem from a lack of knowledge but rather a failure to routinely apply such knowledge in practice.¹³ There are multiple causal factors behind this, such as social pressure, perception of risk, and negative reinforcement cycles, where unsafe behavior goes unpunished until a serious accident occurs.¹⁴ More generally, these factors can be applied to a wide range of public health issues, such as smoking and obesity.

Environmental concerns also can be related to scenarios where individuals know the correct behavior but fail to apply it, leading to effects such as the “tragedy of the commons,” whereby individuals' knowledge of the long-term consequences of their collective actions is outweighed by their short-term individual gain.¹⁵ A range of projects have sought to encourage individuals to lower their consumption by transferring information through play,¹⁶ using location-based services,¹⁷ or applying pervasive approaches that link consumption monitoring to game mechanics.¹⁸ As with healthcare, younger people are a target audience—many serious games tackling power consumption were explicitly developed with such

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However, in some areas, knowledge transfer alone is unlikely to result in significant changes in behavior. One example is road safety, in which studies have shown that in developed

an audience in mind. However, such games might also be used to improve public engagement.¹⁹

Gamification

More generally, gamification might serve as a means to create incentives without incurring costs, rewarding people with virtual trophies, achievements, or other rewards given intrinsic value through peer recognition. Many online communities reward positive behaviors

with such awards, and the interface between a real and virtual community could prove to be fertile ground for exploring how virtual rewards might influence real-world behaviors.

A study of gamification in a mobile context for university students demonstrated both the potential of the approach to engage students and its drawbacks.²⁰ Game-based approaches aren't universally welcomed and, in this case, could be perceived as making a learning resource less valuable—for example, adding game content that trivializes or obstructs the pedagogical content. The “strictness” of game rules and level of difficulty in this case were noted as difficult to apply without leading to usability issues—making the content difficult to access or presenting challenges for creating a usable game interface in addition to the educational design.

Given the recognized importance of usefulness and ease-of-use in technology acceptance,²¹ these findings suggest gamification must be carefully and selectively applied to avoid a negative outcome. This could be achieved by adapting the game to the individual—for example, letting users choose between the initial resource and its gamified form (although this assumes users could introspectively select the ideal resource for their learning needs—a theory partly contradicted by some studies²²). A more comprehensive solution should thus seek to better understand the learner to provide the optimum resource—a task that's the subject of continued research.²³

Across sectors, an important research objective is understanding how to use the rich data collected during play to adapt, personalize, and enhance the impact of serious games on specified behavioral objectives. Effective feedback is central to the efficacy of learning and behavioral outcomes in a range of studies. For example, a minor adjustment to the implementation of feedback during the development of the serious game *Triage Trainer* showed a significant impact on overall efficacy.²⁴

From these findings, we created a model that expresses the multiple levels of game-based feedback using an established generic framework, noting that while games can readily support immediate, evaluatory feedback to learners, higher levels of interpretive, probing, and supportive feedback either require sophisticated machine-driven analysis techniques or the involvement of a training professional. Supporting such professionals, and adopting a tutor-centric as well as a learner-centric view of serious games, are key components of an effective development methodology.²⁵ An experiential viewpoint based on Kolb's established, cyclic model of learning, in which action and experience are met with reflection and conceptualization,²⁶ can be complicated by the level of abstraction a game introduces. To address this feedback, we must recognize and adapt to the learner's capacity to learn independently, as well as ensure a continued match between learner ability and task difficulty, thereby inducing a “flow” experience in which the learner exclusively focuses on task.²⁷

Social Learning

A wide range of studies have sought to examine and identify behaviors unique to social networks constructed in online games. Relationships formed in gaming communities might prove shorter term and less stable than those in nongaming environments, but they might also prove more task-centric and engaging.²⁸ Peer- or e-leader-driven gaming communities might offer another avenue for engendering behavioral change through social learning principles and paradigms.²⁹ As social networks are increasingly used, how these networks might best be understood and used to create models for social change is a topic of ongoing research for the deployment of games.

Case Studies

Here we present two serious games that exemplify how the next generation of

such games might improve the quality of life of individuals experiencing difficulties in human-to-human interaction. We focus on the automatic analysis of (affective) behavior—that is, teaching individuals to “hit the right note” in their verbal and nonverbal expressions, including emotional expressivity, speaking style, and body language.

Autism Spectrum Condition Inclusion

The first example aims to help individuals with Autism Spectrum Conditions (ASC), who often have social communication difficulties and restricted and repetitive behavior patterns. The affinity of most individuals with ASC for a computerized environment has led to several attempts to teach emotion recognition and expression and social problem solving using computer-based training. Because intervention is more effective early in life, a playful serious game approach to support children with ASC could significantly promote their social inclusion.

The European ASC-Inclusion project (www.asc-inclusion.eu) is creating and evaluating the effectiveness of such an Internet-based gaming platform. The ASC-Inclusion software combines a virtual game world with affect and behavior analysis by users' gestures and facial and vocal expressions using a standard microphone and webcam for affective and social behavior training through minigames (see Figure 1). The exercises are partly “karaoke”-style imitation tasks of audio and video clips that display target emotions from private and social categories. Feedback is given, and in free exercises, the children's affect is measured by face, vocal, and body gesture analysis, and information is given to them in a dimensional arousal and valence emotion space.

With a mobile, distributed approach, the children can receive feedback in everyday life situations, and the game can give tasks for real-life social situations. In addition, parents and therapists can

receive online updates and feedback. As a first step in this direction, the game distributes the vocal affect analysis. Additionally, users can play “on the road” on smartphones, because the game runs on an Internet browser.

Social Inclusion and Empowerment of Immigrants

The second example is the European project on mobile assistance for social inclusion and empowerment of immigrants with persuasive learning technologies and social network services (called Maseltov; www.maseltov.eu). The project recognizes the major risks for social exclusion of immigrants from the local information society and identifies the huge potential of mobile services for promoting integration and cultural diversity. Anywhere, anytime pervasive assistance is crucial for more efficient and sustainable support of immigrants.

Innovative social computing services that motivate and support informal learning for the appropriation of highly relevant daily skills can foster language understanding, local community building, and knowledge of cultural differences. These information and learning services are embedded in a mobile assistant—they comprise, for example, ubiquitous language translation, navigation, and administrative and emergency health services, which address activities toward the social inclusion of immigrants in a pervasive and playful manner (see Figure 2a).

In addition to a virtual world, Maseltov develops a mixed reality game in which the user applies his or her language skills in various critical situations, such as shopping and navigating in the urban environment (see Figure 2b). The mobile service helps the user in these situations and receives feedback from the user to measure and estimate performance success. The smartphone senses the success of an applied dialogue in terms of the user’s emotions and frustration in situ, using recent audio-based affective computing.



Figure 1. The European Autism Spectrum Conditions (ASC)-Inclusion project: (a) the virtual game world research camp, where the child plays a scientist researching on emotion, (b) one of the contained minigames (the child must match facial expression and speech by emotion), (c) the karaoke-style emotion training, and (d) a reward (a collectible card with one of several planets and its description).

Advanced human factors studies with wearable interfaces are further applied to extract the decisive parameters of affective- and attention-oriented audio content. Next, data from wearable eye-tracking glasses is interpreted with semantic 3D mapping of attention,³⁰ biosignal sensing, and classification, automatically extracting the decisive parameters for dialogue evaluation. The user can gain credits in the serious game for practicing dialogue.

Maseltov embeds an easily scalable context-recognition framework³¹ that receives input from various context-generating components, such as modules that indicate a current location or the level of learning a host

language. The framework evaluates the user’s behavior and maps it to appropriately motivating actions in the form of recommendations. From long-term dialogue assessments with multimodal mobile context awareness on the basis of affect and attention-sensitive services, the framework classifies the recent migrant’s language learning behavior. The recommender system then instantiates—according to the individual human-factors profile and measured performance—personalized motivating games to change the user’s behavior. For example, to reinforce training on how to interact with local citizens, the system increases rewards for dialogue that supports activities—for example,



Figure 2. The Maseltov mixed-reality game: (a) the virtual world where players first train in a playful way and (b) the pervasive embedding of real-world interactions and tasks that are evaluated for assignments of coins in the virtual world.

by doubling virtual credits in return for dialogue-specific language learning and measured communication in shopping scenarios.

Game Behavior Analysis: Going Mobile

Next we sketch the challenges and opportunities of serious gaming in terms of enabling affect and behavior analysis in mobile and pervasive environments. As the case studies show, analyzing players' behavior, basic emotions, and more subtle "states"—such as interest, confusion, frustration, or stress—can be of vital importance in a serious game. In addition to exploiting a voice recording, we can also exploit video from a smartphone camera³² or physiological measurement from mobile sensors.³³

A particularly engaging form of behavior analysis is to blend the game with real-world events, but this requires the ability to analyze a player's

(affective) behavior "in the wild."³⁴ In particular, it concerns real-time and incremental analysis to provide low-latency system responses to changes in the user's state. A prototype of such real-time, incremental human behavior analysis has been successfully implemented in the Semaine system (www.semaine-project.eu).

Mobile behavior analysis might also foster increased usage. For example, use of automatic speech recognition has greatly increased owing to its deployment in mobile services. In a virtuous circle, its usage in daily life has increased the availability of realistic data for research and development of improved recognition technology and of system self-improvement.³⁵ Thus, implementing mobile behavior analysis applications opens an avenue to remedy the scarcity of labeled, realistic data from the target domain and target users.

Ready-to-use *mobile affect recognition services* are currently emerging. Figure 3 shows a simplified view of a human affect or behavior-recognition system enhanced by a distribution for shared mobile and server processing, as used in the ASC-Inclusion and Maseltov projects. Components in a stand-alone recognizer are depicted in blue, while additional components required for a distributed client-server architecture oriented on the ETSI standard for distributed speech recognition are shown in green.

Recognition System

The affect and behavior recognizer captures the input signals, which can include text, video, or physiological data. The input signals can also include voice data, similar to voice-based input in console games, such as in N64's Voice Recognition Unit, which has been used in *Hey You, Pikachu!*, *Truth or Lie*, *Rainbow Six: Vegas*, Nintendo DS's *Mario Party 6*, and several singing and Microsoft Kinect games. The input is typically captured from sensors such as microphone or camera and is (optionally) preprocessed to enhance the signal of interest in noisy and disturbed conditions.

Low-level descriptors (such as spectral bands or symbols) are extracted on a frame-by-frame basis, where a frame could be some range of time, between 10 and more milliseconds.³⁶ Chunking (segmentation) then refers to the process of grouping frames into meaningful units, such as words or connected movements. This process is optional, if dynamic or recurrent modeling is used in the recognition step. Otherwise, after grouping frames into chunks, functionals such as statistical moments, percentiles, or peaks, can be applied.

Semantic features, such as lexical or action units and other behavioral events, can be converted to a vector space representation, generally resulting in frequencies of occurrence features such as "bag-of-words" vectors. An alternative is to use open-domain

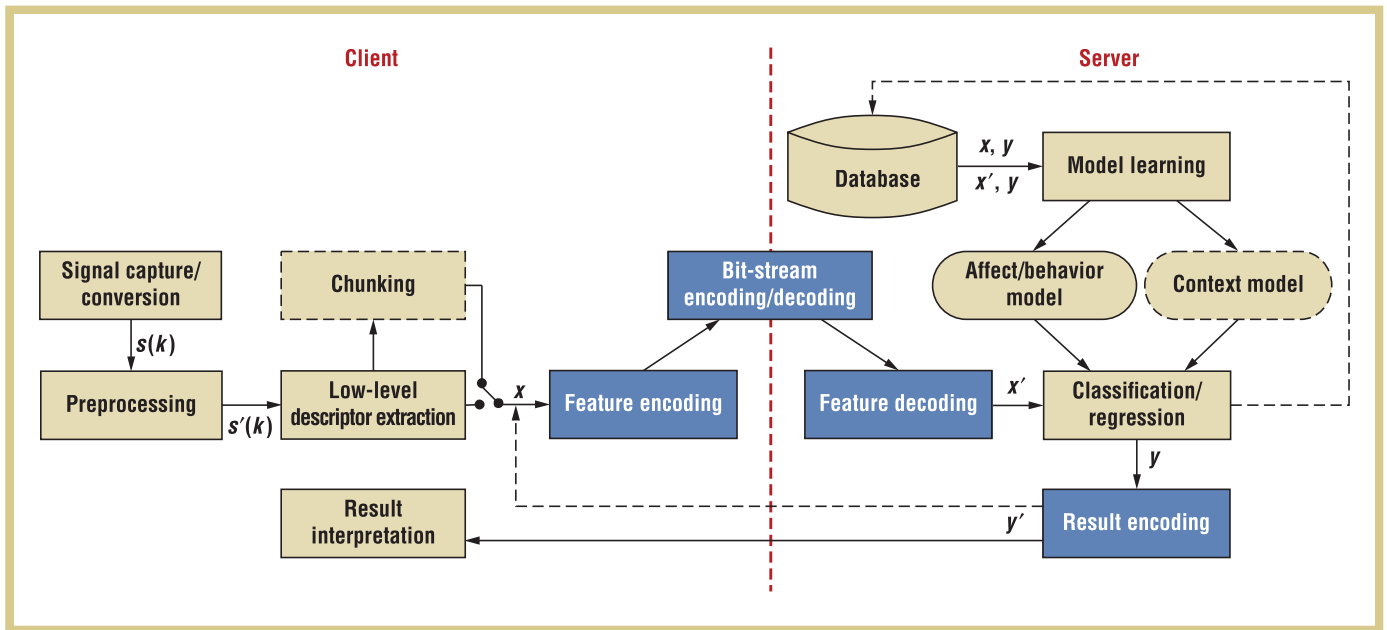


Figure 3. Schema of a mobile affect or behavior analysis system. We use $s(k)$ to represent the signal at discrete time step k , x for the feature vector, and y for the gold standard label. Components in a standalone recognizer are depicted in brown, while additional components required for a distributed client-server architecture oriented on the ETSI standard for distributed speech recognition are shown in blue.

online knowledge sources—for example, to determine the words’ semantic distance from affective or behavioral concepts. In real-time systems, the chunking has to be applied based on human activity detection, which can be already a challenging problem in adverse environments. A database of feature-vector-label pairs is used to train the affect or behavior model and potentially a temporal context model used in classification or regression. First results with affect recognition on autistic children’s speech from the ASC-Inclusion project suggest that binary classification of arousal and valence can be achieved with over 80 percent accuracy, while there’s still room for improvement if a more fine-grained emotion categorization is desired (43 percent accuracy on nine classes). In the context of serious gaming for therapy purposes, these results highlight the necessity of appropriate confidence measures to prevent the system from intervening inappropriately.

Ultimately, the information is forwarded to the game. In the ASC-Inclusion

and Maselto examples, gaming is centered on emotion analysis. In other games, the entry point might be at the control of the dynamic difficulty setting³⁷ or the reaction of nonplayer characters. Alternatively, the game state can also be forwarded to the recognition engine as a contextual knowledge provision—for example, if a stressful or particularly emotional sequence is started.

Distributed Client-Server Architecture

Moving to a distributed architecture can reduce the required transmission bandwidth and decrease storage costs. Information reduction also ensures privacy, because not all (feature) information—such as from a microphone or camera—is transmitted. This is important considering the rather private nature of affect and behavior. Compression rates of 20 to 40 are feasible without significant decreases in accuracy when applying a subvector quantization algorithm.³⁶ Figure 3 shows an important feedback loop from result

encoding to feature encoding, because the distributed architecture lets future mobile services rely on existing mobile services, generating behavioral features and sending them to a server performing affect and behavior recognition, or vice versa.

Ideally, affective user systems should be free in their choice of a server-side recognition engine. Although there are already standards for distributed speech recognition and generic communication protocols, such as Web services, we need standardized feature extraction for affect and behavior recognition in general. Standardizing recognition results to be sent to the client side for interpretation—in this case, the serious game management unit—is currently achieved using markup languages for describing behavior or affective states, such as the W3C’s Emotion Markup Language (EmotionML).

Pursuing affect and behavior recognition “on the go” further implies a need for environmental robustness, particularly against (generally) nonstationary noise sources and

reverberation (in the case of audio analysis) or rotation and low lighting conditions and occlusions (in the case of video analysis). In addition to compensating for such disturbances, distributed recognition will need to cope with various transmission channels and potential package loss. Another important feedback loop found in this system architecture allows continuous system improvement by semisupervised and active learning, which collect better-suited data from the target group for labeling by the system or for crowd sourcing.

Although a system such as the one suggested in Figure 3 has yet to be implemented, several parts already exist: semisupervised learning, evaluation of transmission noise, and noise-robust processing,³⁸ leading to mobile engines.³⁹

Fully automatic affective and behavioral analysis and in-game-feedback are possible with today's technology as long as they're used in "less" serious games or with caretakers and professionals kept in the loop at regular intervals. In particular, pervasive solutions can train the user in a playful way in everyday life situations and allow close-to-real-life simulations. This requires bringing affect and behavior analysis "on the road," which leads to new research questions, such as how to ensure low energy consumption or exploit situational context knowledge based on location sensitivity.

Furthermore, the rapid growth of social networks increasingly offers a platform for deploying games to numerous users. Ethical methods for data capture from these users, coupled with analysis techniques for interpreting the resultant "big data" and subsequently adapting the game, will play an increasing role in delivering more efficient and targeted solutions. In parallel, going from mobile to pervasive computing will, in

particular, address the questions of localized scalability. In the long run, "invisibility" can then be reached in the sense that the gaming blends into the real world in a positive sense—the game stops unnoticed and the learned behavior persists.

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Björn W. Schuller is a visiting key researcher at Joanneum Research Forschungsgesellschaft mbH in Graz/Austria and a tenured senior lecturer at Technische Universität München in Munich/Germany. His research focuses on affective computing and computer audition. Schuller received his habilitation and doctoral degree in electrical engineering and information technology from Technische Universität München. He is coordinator of the European ASC-Inclusion project and the European Cluster for Digital Games for Empowerment and Inclusion. Contact him at bjoern.schuller@joanneum.at.



Ian Dunwell is a senior researcher at Serious Games Institute, Coventry University. His research principally focuses on the development and application of effective design and evaluation methods for serious games. Dunwell received his doctorate degree in computer science from The University of Hull. Contact him at idunwell@cad.coventry.ac.uk.



Felix Weninger is a researcher in the Machine Intelligence and Signal Processing Group at the Institute for Human-Machine Communication at Technische Universität München. His research focuses on environmental robustness and software engineering of real-world speech analysis applications. Weninger received his diploma in computer science from Technische Universität München. Contact him at weninger@tum.de.



Lucas Paletta is a key researcher at Joanneum Research Forschungsgesellschaft mbH in Graz/Austria, leading a research studio on human factors technologies and services. His research focuses on mobile and wearable context awareness and computational attention. Paletta received his doctoral degree in computer science from Graz University of Technology. He is the coordinator of the European Maseltov project. Contact him at lucas.paletta@joanneum.at.

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