

Analysing Performance in Authentic Digital Scenarios

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Abstract When components of authentic learning are enabled by technology and the event-level interactions of learners are recorded as a historical stream of items, a voluminous and varied data record of the performance in the scenario rapidly accumulates into a transcript. This transcript, the context in which it was created, and based on it, the purposes, intentions, and practical utilities of making interpretations and inferences about what someone knows and can do is key to analysing performance in authentic digital scenarios. However, an effective assessment system not only provides a signifier of what people know via a classification and token such as a grade or badge, but also provides evidence of actions, artefacts, and processes, how knowledge was formed over time, and how well the person is able to apply the knowledge in specific situations.

Keywords Performance assessment • Digital scenario • Authenticity • Real-world problem

1 Defining Authentic Scenarios and Digital Interactions

In order to set the stage for a discussion of recent analyses of performance in authentic digital scenarios, we define two terms: *authentic performance* and *digital interactions*. Authenticity is an important criterion for observing and analysing a digital performance, because the validity of observable evidence of knowledge (i.e. the acquisition, possession, and application of declarative as well as procedural knowledge) is provided by actions (e.g. making, doing, enacting, and communicating) situated in a particular context or scenario (e.g. collaborative problem-solving) and culture (e.g. a science or humanities) (Brown et al. 1989;

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Rosen 2015). Four recognized components of authenticity are real-world problems, inquiry learning activities, discourse in a community of learners, and student autonomy (Rule 2006) which are elaborated below.

When we refer to *digital interactions*, we are referring specifically to data inputs collected by an interactive computational application that either come directly from the learner or secondarily from aggregations of those inputs. A mouse click, tracked eye movement, and keyboard press are examples of direct event-level interactions, and a group of such actions, such as forming a word with keyboard presses or organizing screen resources into a priority order by dragging and dropping them onto an image, are examples of aggregated sets of actions (Ifenthaler and Widanapathirana 2014; Nasraoui 2006). When the components of authentic learning are enabled by technology and the event-level interactions of learners are recorded as a historical stream of items, a voluminous and varied data record of the performance in the scenario rapidly accumulates into a transcript (Berland et al. 2014; Romero and Ventura 2015).

This chapter addresses that transcript, the context in which it was created, and based on it, the purposes, intentions, and practical utilities of making interpretations and inferences about what someone knows and can do.

2 Criteria for Authentic Digital Scenarios

Building on the two definitions presented above, we propose criteria for authentic digital scenarios as those in which an activity is situated in a cultural practice (Young 1993).

- *Real-world* problems that engage learners in the work of professionals are also referred to as ‘epistemic frames’ (Shaffer 2006) which are knowledge community’s ways of knowing, valuing, and expanding their body of knowledge. We might think of this criterion of authenticity as the ‘social epistemology’ of the scenario, which highlights the role of the community of practice (Bransford et al. 2000; Grotzer et al. 2015) in maintaining and recognizing creative innovations in a body of knowledge (Csikszentmihalyi 1996).
- *Inquiry* activities that provide practice with thinking skills and metacognition involve autonomy, exploration, and creative application of concepts during problem-solving (Caliskan 2012), leading to deeper learning via self-directed construction and increasing competence of one’s mental models (Ifenthaler and Seel 2013).
- *Discourse* among a community of learners provides discipline-focused interactions and relatedness as a context for situated learning, practice, and assessment and supports the growth of expertise (Hickey and Zuiker 2012; Lave 1991).

- *Autonomy*, empowerment, and self-efficacy are enhanced through choice and control (Bandura 1997; Eseryel et al. 2014). Choice supports autonomy and, when combined with competence and relatedness, yields enhanced self-motivation and mental health, which are essential for positive decision-making and self-directed learning (Ryan and Deci 2000).
- *Unobtrusive measures* capture the direct and aggregated *digital interactions* in the performance without disturbing natural thought and action situated with the components (Clarke-Midura et al. 2010; Dummer and Ifenthaler 2005; Webb et al. 2013).
- *Timely observations* based on the measures, both automated and human (which implies feedback loop and possibility for user action), are made with a minimum of disturbance to the context, culture, and activity (Ifenthaler 2014; Ifenthaler and Widanapathirana 2014).

We combine these criteria and definitions into the concept of an *authentic digital performance space* designed with an educative purpose. The authentic digital performance space subsumes what others have called a *virtual performance assessment* when the purpose is focused on replacing less-authentic traditional testing (Clarke-Midura et al. 2012; Ifenthaler et al. 2014). Examples of other purposes of the generalized authentic digital performance space include research and development of:

- Knowledge maps of learners under a variety of conditions (Hanewald and Ifenthaler 2014; Ifenthaler 2010a; Ifenthaler and Pirnay-Dummer 2014),
- Challenges and issues of network analysis (Ifenthaler 2010b; Shaffer et al. 2009),
- Evolution of digital spaces enhanced by participatory teaching and learning methods (Gibson 2010),
- New psychometrics of digital performance spaces (Behrens et al. 2012; Eseryel et al. 2013; Gibson and Clarke-Midura 2015; Ifenthaler et al. 2012),
- Quality automated formative feedback in scalable online learning (Ifenthaler 2011; Webb and Gibson 2015),
- Understanding the social utility of the affordances such as space for collaboration (Rosen 2014, 2015).

Research is needed on the application of the criteria to levels of authenticity that result from variations in the criteria. For example, is it sufficient to have a near-real-world experience with a low level of choice? Is it effective to have high levels of discourse with low levels of inquiry? To what degrees do various levels of obtrusive measures impact one's performance? We will assume that there will be observable impacts of low levels or absence of any of the criteria (or corresponding high levels of interference with the criteria) on the authenticity of the scenario and someone's performance in the scenario (see Table 1).

Table 1 Examples of impacts of authentic digital scenario criteria

Criterion	When missing	When present
Real world	Irrelevance, distant or future need to know, simplicity, minimum cognitive load	Immediacy of need to know, complexity, maximum cognitive load
Inquiry	Received passive knowledge	Constructed active knowledge
Discourse	Individual misconceptions are not surfaced or challenged	Mental models are socially validated
Autonomy	Lack of freedom and control	Increased self-direction and motivation
Unobtrusive measures	Interrupted decontextualized performance	Natural application of knowledge-in-action
Timely observations	Feedback not available to improve performance	Micro-adjustments and incremental improvement

3 Digital Interactions as Evidence of Authentic Performance

Evidence is interpretation of data to make a claim. What we are concerned with here is how digital interactions can be interpreted as evidence for the claim of authentic performance given the criteria outlined above. A foundational model for interpretation is given by evidence-centred design or ECD (Mislevy et al. 2006) in which a chain of reasoning flows from evidence collected at one level (e.g. atomistic events) to inferences and claims about the learner at another level (e.g. aggregations, comparisons, and interpretations). The inference can be remote from the evidence in both space and time, as when a post hoc analysis makes a claim or when someone reflects on what they learned from a past experience.

The path from events to inferences is defined and bounded by an ECD model of *a representative performance that has been validated by subject domain experts*. The model of performance then supports a chain of inference that leads from events to justified interpretations based on that evidence. The ECD modelling process includes domain analysis, domain modelling, constructing a virtual performance space with a conceptual assessment framework, and then implementing and delivering a prompt or virtual performance space that elicits authentic performance (Mislevy et al. 2006).

Before further considering interpretation and inference, note that a nearly complete performance can be replayed to some particular level of representational accuracy by replaying the transcript of the digital record. This is a unique affordance of an authentic digital performance that is generally less available in real-world performances, even when documented by video recording. Similar to a video recording of a real-world performance, a digital record is always taken from a particular perspective through a focusing lens that captures only the external portions of the events (e.g. not a complete picture of the mental models and representations of the actors) (Ifenthaler 2008). So partiality in interpretation and

inference are ever-present. Human interpretation, consumption, and responsive action are therefore common objectives of analysis in both real and virtual situations. With replay, partiality, and human interpretation in mind, we are nevertheless concerned with codifying and automating as much as possible so that multiple levels of analysis can be extracted and entrained from the physical record and multiple interpretations can be supported by evidence.

Analyses of the performance transcript, even when automated and multileveled, are a mixture of *conditional and inferential interpretation* that can utilize several frames of reference while adding layers of interpreted evidence, insights concerning the complexity and additional dimensionality to our understanding of the performance and our ability to represent the performance in the light of our understandings. A conditional interpretation is one made with partial and incomplete knowledge (Pereira and Pollack 1991). For example, in natural language processing, the rules of how phrases fit together help determine the possible interpretations of parts of an utterance, but the complete meaning only becomes evidence as the rest of the context and the complete utterance becomes available (Indurkha and Damerau 2010). We might think of the process as a drawing that we are watching take shape, where initial outlines of a sketch might be abandoned and new lines filled in with details at a later stage of the observation. Once complete information is available, or a ‘stop’ occurs in the observations, then a summative judgment or inferential interpretation represents the best we can do with the available information. We describe this process below as part of an assertion that *exploratory data mining is a necessary initial stage of research into a new digital performance space*.

3.1 Evidence-Centred Claims

Claims about what someone knows and can do based on an assessment are supported by a chain of reasoning or argument leading from data to the claim, which is in turn supported by warrants (e.g. hypotheses or truth statements) and backing (e.g. historical data). A claim can face a counterargument supported by alternative hypotheses and rebuttal data (Mislevy et al. 2003).

Establishing validity entails making the warrant explicit, examining the network of beliefs and theories on which it relies, and testing its strength and credibility through various sources of backing. It requires determining conditions that weaken the warrant, exploring alternative explanations for good or poor performance, and feeding them back into the system to reduce inferential errors (Mislevy et al. 2003).

3.2 Designing a Claim

The conceptual assessment framework has three core components: the student model, task model, and evidence model within and among which the time-sensitive relationships adhere (Mislevy et al. 2006). The measurement problem for authentic

performance in a digital space is, by this theoretical framework, how to compare an actual to an expected performance (i.e. student model), how to take stock of the situation or prompt that evokes that performance (i.e. task model), and, from these sources of information, how to build a defensible inference from the evidence in a complex performance environment (i.e. evidence model).

Accordingly, the classification system of an assessment of a digital performance has to handle *patterns of simultaneous and sequential interactions* as well as a *hierarchy of relationships in a complex network* in order to make valid links to time-sensitive evidence rules within the conceptual assessment framework (Gibson and Jakl 2015).

4 Primary Challenges of Digital Performance Analysis

An effective assessment system not only provides a signifier of what people know via a classification and token such as a grade or badge, but also provides evidence of actions, artefacts, and processes, how knowledge was formed over time, and how well the person is able to apply the knowledge in specific situations (Baker 2007).

Over the last 25 years, the analysis of the learning-dependent construction and progression of knowledge has been discussed extensively (Johnson-Laird 1989). Still, reliable and valid assessment techniques for capturing changes in knowledge structure are still being developed (Baker et al. 2008). We note that knowledge is internal and its representations are internal (Ifenthaler 2010b). A direct assessment of these internal knowledge representations is therefore not possible, and different types of knowledge structure require different types of representations. The inter-relationships between internal knowledge structure and external analysis artefacts can be described by distinguishing three zones—the object zone W as part of the world, the knowledge zone K , and the zone of internal knowledge representation R (Ifenthaler 2010b). In addition, performance analysis must rely on two functions: (1) f_{in} as the function for the internal representation of the objects of the world (internalization) and (2) f_{out} as the function for the external re-representation back to the world (externalization) (Ifenthaler 2010b). Neither class of functions (f_{in} , f_{out}) is directly observable. Accordingly, performance analysis requires a dual process of encoding (Galbraith 1999; Wygotski 1969). Within internal encoding, a mental model is constructed out of one's actual available world knowledge in order to create subjective plausibility (Ifenthaler and Seel 2013), i.e. a mental model is represented as an internal knowledge structure. The actual performance analysis occurs through communication of knowledge structure requiring the use of adequate sign and symbol systems but also a format of communication, which the performance analysis environment requires. Clearly, these complex cognitive processes result in a biased measurement of knowledge representation as researchers are currently not able to more precisely define the above-described functions of internalization and externalization. Finally, within digital environments the possibilities of authentic knowledge externalization and performance analysis are limited

to a few sets of sign and symbol systems, namely graph-based and language-based approaches (Ifenthaler and Pirnay-Dummer 2014).

Inferring what someone knows and can do based on digital interactions thus depends on the affordances of the game or other e-learning experience *as a performance space for assessment* (Mayrath et al. 2012). Combining *digital performance* with *performance assessment*, this concept of a gamified e-learning experience includes all types of performance in which computer technologies have taken on a primary rather than an auxiliary role in the content, techniques, aesthetics or the delivery of someone's expression, and where the digital record is used as evidence of learning. The concept implies new challenges for psychometrics due to the increased complexity of the digital record (Ifenthaler et al. 2014). At the atomistic level, performance data issues include time and event segmentation, cyclic dynamics, multicausality, intersectionality, and nonlinearity. At the summary level, the key challenge is model building and providing authentic real-time feedback (Gibson and Jakl 2015).

5 Conclusion

Assessing simple problem-solving is straightforward since there is usually a single correct answer to such problems (Funke 2012). However, analysing performance in authentic digital scenarios is more challenging because authentic real-world problems do not have standard correct answers and often require expert teams interacting over a longer period of time to develop and perform a solution (Eseryel et al. 2013). Accordingly, a large record of data about the context of the authentic digital scenario and the actual performance of an individual or a team needs to be stored and analysed in real time. This requires intelligent adaptive algorithms of learning analytics in order to enable meaningful analysis as well as personalized and adaptive feedback to the learner.

Such algorithms for personalization have been developed; however, only a few have been implemented in educational settings (Drachsler et al. 2008): 1. Neighbour-based algorithms recommend similar learning materials, pathways, or tasks based on similar data generated by other learners. 2. Demographics algorithms match learners with similar attributes and personalize the learning environment based on preferences of comparable learners. 3. Bayesian classifier algorithms identify patterns of learners using training sets and predict the required learning materials and pathways. In addition, these algorithms have several shortcomings. First, they are not sensitive to semantic characteristics of the learner and the learning environment. Second, they lack validity in fully automated learning environments. Third, empirical evidence focussing on benefits for learning is scarce (Ifenthaler and Widanapathirana 2014). Forth, the acceptance of fully automated systems among learners is limited.

To conclude, analysis of performance in authentic digital scenarios could benefit from semi-automated implementation of personalized learning environments at scale.

Such an approach could include machine learning algorithms (MLA) that are continuously shaped by human actions (e.g. teachers, the learners themselves, experts, and others). The ratio between MLA and the human for personalizing the learning environment depends on a) the available data in the system (e.g. learner characteristics, prior knowledge, learning patterns recognized), the subject domain as well as the task complexity and competence or performance level to be achieved. Accordingly, MLA will assist intelligent digital scenarios in making decisions for personalized learning environments and teachers will validate recommendations by MLA.

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Author Biographies

David Gibson is Associate Professor or Director of Learning Engagement at Curtin University in Australia, and he received his Ed.D. from the University of Vermont in Leadership and Policy Studies in 1999. His foundational research demonstrated the feasibility of bridging from qualitative information to quantifiable dynamic relationships in complex models that verify trajectories of organizational change. He provides thought leadership as a researcher, professor, learning scientist, and innovator. He is creator of simSchool, a classroom flight simulator for preparing educators, and eFolio an online performance-based assessment system, and provides vision and sponsorship for Curtin University's Challenge, a mobile, game-based learning platform. His research has extended from learning analytics, complex systems analysis, and modelling of education to application of complexity via games and simulations in teacher education, web applications, and the future of learning. Dr. Gibson has also advanced the use of technology to personalize education via cognitive modelling, design, and implementation. His articles and books on games and simulations in learning led to applying game-based learning principles to the design and implementation of *The Global Challenge Award* a cyber-infrastructure-supported global problem-solving contest for students from 100 countries while a Research Professor of Computer Science at the University of Vermont, College of Engineering and Mathematical Sciences.

Dirk Ifenthaler is Adjunct Associate Professor at Curtin University, Australia, and Affiliate Research Scholar at the University of Oklahoma, USA. His previous roles include Professor and Director, Centre for Research in Digital Learning at Deakin University, Australia, Manager of Applied Research and Learning Analytics at Open Universities, Australia, and Professor for Applied Teaching and Learning Research at the University of Potsdam, Germany. He was a 2012 Fulbright Scholar-in-Residence at the Jeannine Rainbolt College of Education, at the University of Oklahoma, USA. Dirk Ifenthaler's research focuses on the intersection of cognitive psychology, educational technology, learning science, data analytics, and computer science. He developed automated and computer-based methodologies for the assessment, analysis, and feedback of graphical and natural language representations, as well as simulation and game environments for teacher education. His research outcomes include numerous co-authored books, book series, book chapters, journal articles, and international conference papers, as well as successful grant funding in Australia, Germany, and USA—see Dirk's website for a full list of scholarly outcomes at www.ifenthaler.info. Dirk Ifenthaler is the Editor-in-Chief of the Springer journal Technology, Knowledge and Learning (www.springer.com/10758). He is the Past-President for the AECT (Association for Educational Communications and Technology) Design and Development Division, Past-Chair for the AERA (American Educational Research Association) Special Interest Group Technology, Instruction, Cognition and Learning, and Co-Program Chair for the international conference on Cognition and Exploratory Learning in the Digital Age (CELDA).

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