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Factor Analysis of a Generalized Video Game Experience Measure

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Abstract

Video gaming experience has been found to impact behavior and performance on experimental tasks, can influence cognitive processes, and may even transfer to proficiency in novel tasks. There is a growing need for an empirically validated generalizable tool that can capture differences in participants gaming experience due to the growing representation of regular video gamers, and the proliferation of gamified, simulated task environments. The analyses reported here examine the factor loadings of a general Video Game Experience Measure (VGEM) designed to tap facets of gaming experience that can distinguish non-gamers from gamers and is also sensitive to varying levels of proficiency. Results from exploratory and confirmatory factor analyses find support for a five-factor model capturing: Game-skill Confidence, Gaming Lifespan, Gaming Intensity, Gaming Frequency, and Gamer Self-efficacy. These findings are discussed in the context of how the VGEM can support research using gamified task environments requiring the study of cognition and collaboration.

Keywords

Psychometrics and testing, Games, Simulation and virtual reality

Introduction

The ability to accurately assess video game player capabilities based upon their experience has implications, not only for the video game industry, but also for experimental research. Simulated task environments have become increasingly ubiquitous across fields of human-centered research. Largely, this is due to the utility of synthetic test environments and gamified tasks for not only assessing participant actions and performance, but also engaging their interest and promoting more naturalistic behavior (Cooke et al., 2017). Being able to characterize players and interpret their behaviors can certainly benefit the gaming industry, but, more importantly, it is critical for researchers to understand the impact that an individual's video game experience may have on their personal performance in facets of cognition such as attention and reaction time, as well as on their social-cognitive behaviors (e.g., interactions in teams).

Studying the relationship between cognitive and collaborative behavior, while accounting for video game experience is particularly relevant for near-future teams that are likely to feature virtual, artificial, and possibly autonomous team members. Research on highly virtualized, as well as human-autonomy teams, is much more viable in simulated, virtual testing environments. Further, the ability to understand and explain player behavior can afford an artificial social intelligence (ASI) the ability to interpret and predict the actions they choose to take (Williams et al., 2022). For example, with the increasing use of simulation in human-agent research (e.g., Freeman et al., 2021), research can examine how an ASI can leverage a priori information about players to develop models that are able to anticipate human behaviors. Further, the ability to accurately assess video game experience can help address problematic variance that comes from the use of individuals who play video games habitually and who are able to perform better than control populations on novel tasks. Green and Bavelier (2012) proposed a model positing that video gamers have acquired an ability to learn the mechanics and features of novel tasks, and games, more quickly than those who do not player video games (Bavelier et al., 2012; Green and Bavelier, 2012). Some studies have found support for this "learning to learn" model, but studies suggest it varies depending on the cognitive demands required by the task (Smith et al., 2020).

Currently, approaches to measure video game experience are typically not empirically validated, and rather than aiming to capture skills or abilities player's developed through

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video game play, these measures often focus on player motivations to play, player experience and enjoyment while playing, and examining the effects or consequences of video game play on players. For example. early research in player experience (Bartle, 1996), created Multi-User Dungeon profiles, which consisted of four basic player types that categorized different motivations for play. Yee (2006) took a similar approach, examining motivation for play in the Massive Multiplayer Online Role Playing Game (MMORPG), World of Warcraft. Norman (2013) compared development of a measure by Brockmyer et al. (2009) and IJsselsteijn et al. (2013). Brockmyer et al. focused on negative issue of violence in video games, whereas IJsselsteijn et al. studied the gaming experience itself. Brockmyer et al. developed their questionnaire over several testing iterations and validated the psychometric properties of the questionnaire prior to using it in the field, whereas IJsselsteijn et al. had not validated or published any empirical results of using the measure or the psychometric evaluations of its reliability and validity (Norman, 2013). Despite the fact that IJsselsteijn et al.'s measure lacks a formal peer-reviewed publication, it is widely applied in games research (Law et al., 2018), highlighting the need for empirical validity in player assessment. There are others who have developed validated measures that demonstrate empirical validity, such as the Gameful Experiences Questionnaire (GAMEFULQUEST; Högberg, 2019) and the Ubisoft Perceived Experience Questionnaire (UPEQ; Azadvar & Canossa, 2018). Whether or not validated, these tend to be motivated by a desire to assess a player's experience, or the player's self-reported perceived enjoyment, satisfaction, engagement, immersion, etc. with regards to a game or a dimension of a game's experience (Abeele et al., 2020). Further, in seeking objective data in player research, some studies have employed physiological measures such as heart-rate, electroencephalography, electromyography, but these methods increase the financial and time costs of research and can be difficult to interpret (Johnson et al., 2018). The techniques available to consider behavioral data range from simple aggregate statistics to machine learning, with each having its own respective strengths and weaknesses, and providing its own insights into player behavior (Sifa et al., 2017).

In sum, the multi-faceted nature of player experience as well as differing conceptual theories regarding the various constructs present a problem that has led to the development of multiple scales that measure the same constructs, very few of which have been fully empirically validated (Johnson et al., 2018). Though there are multiple measures of video game experience that have been developed, these measures tend to suffer from challenges in validity and reliability, such that peer-reviewed, empirical validation of even the most commonly used scales are limited or absent. Thus, there is a need in both industry and academia to attempt to provide data-driven insights into player behavior (Sifa et al., 2017).

Purpose

Because of the limitations of current methods for measuring a participant's video game play experience (for further discussion on this, see: Bendell et al., 2021a; Williams et al., 2021) in a way that can account for performance differences, and that has been empirically validated (Abeele et al., 2020), we developed a tool that could potentially fill this gap. This was done in the context of a larger research program, the Defense Advanced Projects Research Agency's "Artificial Social Intelligence for Successful Teams" (ASIST; DARPA, 2019). To help us better understand player experience on teams coached by AI, in the Minecraft gaming environment, we developed a measure that captures a variety of video game experience components. Iteratively and in collaboration with other ASIST program performer teams (including from partners in the program, e.g., IHMC and Gallup), we devised a measure with the goal of capturing facets of participant performance that can provide a priori information to an agent capable of "artificial social intelligence" (ASI). We report on factor analyses on the Video Game Experience Measure (VGEM), tested using data collected under DARPA's ASIST program. With data from the ASIST study two (Huang et al., 2021), we conducted an exploratory factor analysis, and using data from the third study, we conducted a confirmatory factor analysis, to examine the use of this measure across two studies.

Gamed-based Experimental Task: Minecraft Urban Search and Rescue

As part of DARPA's ASIST program, the experimental task was designed as a simulated urban search and rescue (USAR) operations. It involves teams of players taking on different roles to locate and rescue victims of a building collapse. The task was completed in a gamified virtual environment that was developed based on the foundational platform afforded by Minecraft (Mojang, 2015).

Video Game Experience Measure (VGEM) Items

Video game experience measures typically are devised to suit specific researchers' needs, so measures range from short or single item scales to batteries aimed at capturing player's motivations, preferences, and, typically self-reported, proficiency. This video game experience measure attempts to utilize items targeting general video game experience with items capturing facets of experience related to the specific experimental task. This experience measure has been refined over multiple studies to focus on four primary facets of an individual's gaming experience: skills acquired through exposure, length/duration of exposure, intensity of exposure, and self-perceived proficiency/expertise. Through capturing both general and task specific experience, we sought to capture a more comprehensive picture of experience.

A full version of the refined video game experience measure can be reviewed at the ASIST study 2 project's online open science framework record (Huang et al., 2021); however, with regards to the facets mentioned above, examples of items include "General: Years using a computer to play video games" "Specific: Years playing Minecraft (any expansion or version)" and "General: Please indicate how regularly you: Play video games which require participation in a team" and "Specific: For the following, please indicate how regularly you: Play Minecraft" perceived skill/proficiency includes "Specific: Indicate the level of mastery you have over the following skills as compared to other video gamers that you know or have played with: Maintaining an awareness of game/task parameters (e.g., time limits, point goals, etc.)." The measure administered to participants in these studies contained 24 items after reduction and refinement of items.

Methods

The data analyzed here was collected by Arizona State University as part of the Artificial Social Intelligence Supporting Teams project's second experimental study (referred to as Study 2) and represents a portion of a larger dataset (available here: Huang et al., 2022). The study utilized multiple survey measures that capture various aspects of participants such as personality and social intelligence – of note for the present analyses were surveys related to demographic information as well as video game experience. Our interest is primarily on the value of these measures, namely video game experience, as a potential predictor of experimental task performance.

ASIST Study 2

Participants. The current analyses use a subset of the entire ASIST dataset (a description and data files of the entire ASIST data collected is available here: Huang et al., 2022). The study collected 67 teams of three individuals, with three teams were removed due to errors in experiment administration, leaving 192 participants in the remaining sets. Of those 192 participants, some were removed due to incomplete or missing data, leaving 132 participants in the analyses reported here. The sample was predominantly male, 128 males and 46 females, and young, minimum 18 years old and maximum 49 years, with an average of 21.9 years

Procedure and Materials. A description of the experimental task in this study will be summarized briefly (for a complete description of procedure and materials, see: Huang et al, 2021). The experimental task was a game-based team urban search and rescue missions, in which participants performed two missions as a member of a three-person team. The video game experience measure contained a total of 24 items, though only 3 of these were removed as they were strictly capturing Minecraft-specific video game experience instead of more generally applicable video game experience that could be employed to assess video game experience in other contexts. It is noted, however, that specific video game experience can be a useful in determining the level of a participant's experience (see Bendell et al., 2021a). Participants completed the video game experience as part of a set of surveys during the first phase of the study. Following the completion of those surveys participants underwent task training including hands-on training and tests of comprehension and competency. Then teams of participants were tasked with completing two, 10-minute Minecraft USAR missions (see brief on mission characteristics in "Game-based Experimental Task: Minecraft USAR" above). Between the two missions and after the second, participants responded to additional surveys about teamwork.

Results

Exploratory Factor Analysis

To explore the factorial structure of the generalized computer video game experience measure, all 21 items of the instrument were subjected to an exploratory factor analysis with oblique rotation (oblimin). The Kaiser-Meyer-Olkin measure verified the sampling adequacy for the analysis, KMO = 0.854. Bartlett's test of sphericity χ^2 (210) = 1840.43, $p <$ .001, indicating that correlation structure is adequate for factor analyses. The maximum likelihood factor analysis with a cut-off point of .40 and the Kaiser's criterion of eigenvalues greater than 1 yielded a five-factor solution as the best fit for the data, accounting for 56.4% of the variance (RMSEA = 0.064). The results of this factor analysis are presented in Table 1 and Table 2.

In our measure, a five-factor model emerged in the exploratory factor analysis. The first, Factor 1, Game-Skill Confidence, is related specific skills that a player can possess, and their confidence in being able to learn and obtain new skills. Factor 2, Gaming Lifespan, is related to an individual's prior history with computers and video games overall. Factor 3, Gaming Intensity, seems to be tapping into an individual's propensity to play games regularly, seriously, and competitively as can be seen through the negative relation to Motivation, wherein low scores corresponded with "playing for achievements, competition, mastery", focusing on maximizing score, optimizing teamwork through relevant team-related skills. Factor 4, Gaming Frequency, is related to an individual's current gameplay habits in terms of frequency of gameplay. Factor 5, Gamer Self-efficacy, can be considered an individual's self-perceptions of their gameplay skills and abilities, such as whether they view themselves as a novice, intermediate, advanced, or expert player as compared to others.

Table 1. Exploratory Factor Analysis of the VGEM Items.

VGEM item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Skill:TrackPathing	0.888					0.305
Skill:LearnLayout	0.838					0.329
Skill:TrackLocation	0.823					0.264
Skill:LearnItems	0.764					0.466
LearnerConfidence	0.731					0.454
Skill:TaskAwareness	0.666					0.507
Skill:CommLocation	0.577		0.404			0.362
Skill:CoordinateTeam	0.531		0.409			0.405
Skill:WASDcontrol	0.519					0.637
Years: ComputerUse		0.946				0.159
Years: ComputerGames		0.799				0.434
Years: NonComputerGames		0.574				0.593
Frequency: TeamGames			0.700			0.336
CompetitiveGame			0.565			0.499
Motivation			–0.488			0.763
Frequency: ComputerGames				1.017		0.005
Frequency: VideoGames				0.539	0.431	0.451
PercievedExperience					0.785	0.167
PercievedProficiency					0.650	0.337
Freuqnecy: NonComputerGame						0.883
ControlPreference						0.864

Note. Extraction method: maximum likelihood; Applied rotation method is promax. Loadings larger than .40 are shown.

Table 2. EFA Factor Characteristics.

	Unrotated solution			Rotated solution		
	SumSq. Loadings	Proportion var.	Cumulative	SumSq. Loadings	Proportion var.	Cumulative
Factor 1	6.427	0.306	0.306	4.913	0.234	0.234
Factor 2	2.081	0.099	0.405	1.867	0.089	0.323
Factor 3	1.701	0.081	0.486	1.674	0.080	0.403
Factor 4	0.931	0.044	0.530	1.672	0.080	0.482
Factor 5	0.702	0.033	0.564	1.655	0.079	0.561

ASIST Study 3: Confirmatory Factor Analysis

Participants. The current analyses use a subset of the entire ASIST dataset (a description and data files of the entire ASIST data collected is available here: Huang et al., 2022b). Study 3 data consists of 336 participants. The sample was predominantly male (259), 66 were female, 6 were nonbinary, and 5 preferred not to say. Participants were also young, a minimum of 18 years old and maximum of 66 years old, with an average of 22.8 years old.

Procedure and Materials. The experimental task in Study 3 is very similar to Study 2, though there are some differences with regards to game mechanics. A full description of the experimental task in this study is outside of our scope for the purposes of the confirmatory factor analysis (for a complete description of Study 3 procedure and materials, see: Huang et al, 2022a).

Confirmatory Factor Analysis. Due to space limitations, only the details of the full 5-factor model are reported here. Additional analyses were conducted to investigate the validity of a 3-factor (combining factors 2 and 4 as well as 3 and 5) and two separate 4-factor models (combining factors 2 and 4, and separately combining factors 3 and 5). Fit indices for the additional models did not suggest that the 4-factor models were more suited than the 5-factor, but the 3-factor may be an appropriate fit if not better than the full 5-factor. The preliminary analyses reported here discusses the full 5-factor model from which the others may be derived.

The five-factor model, which had emerged in the exploratory factor analyses associated with ASIST Study 2, was

Table 3. CFA Factor Loadings.

Factor	Indicator	Sym.	Est.	Std. error	z-value	p	95% Conf. Interval	
							Lower	Upper
Factor 1	Skill: LearnLayout	$\lambda 11$	14.245	0.479	29.741	$< .001$	12.182	16.084
	Skill: CommLocation	$\lambda 12$	16.715	0.609	27.460	$< .001$	14.686	18.869
	Skill: CoordTeam	$\lambda 13$	14.864	0.524	28.355	$< .001$	12.309	17.338
	Skill: TaskAwareness	$\lambda 14$	13.269	0.455	29.171	$< .001$	11.407	15.118
	Skill: LearnItems	$\lambda 15$	12.997	0.469	27.715	$< .001$	10.411	15.097
	Skill: TrackPathing	$\lambda 16$	12.855	0.502	25.620	$< .001$	11.000	14.854
	Skill: WASDcontrol	$\lambda 17$	10.340	0.371	27.834	$< .001$	7.860	12.899
	Skill: TrackLocation	$\lambda 18$	14.152	0.498	28.413	$< .001$	12.273	16.120
	LearnerConf.	$\lambda 19$	17.506	0.550	31.820	$< .001$	14.747	20.431
Factor 4	Frequency: VideoGames	$\lambda 21$	0.937	0.029	32.294	$<.001$	0.867	1.018
	Frequency: ComputerGames	$\lambda 22$	0.813	0.025	32.294	$<.001$	0.867	1.018
Factor 2	Years: ComputerUse	$\lambda 31$	2.435	0.202	12.048	$<.001$	1.742	3.057
	Years: ComputerGames	$\lambda 32$	3.352	0.261	12.827	$<.001$	2.463	4.253
	Years: Non-ComputerGames	$\lambda 33$	4.229	0.296	14.277	$<.001$	3.270	5.234
Factor 3	Frequency: TeamGames	$\lambda 41$	0.783	0.031	25.648	$<.001$	0.681	0.879
	Motivation	$\lambda 42$	-0.322	0.030	–10.792	$<.001$	–0.478	–0.181
	Competitive-Game	$\lambda 43$	0.704	0.028	44.899	$<.001$	0.620	0.786
Factor 5	Perceived Proficiency	$\lambda 51$	0.940	0.021	44.899	$< .001$	0.899	0.977
	Perceived Experience	$\lambda 52$	0.953	0.021	44.899	$< .001$	0.916	0.994

Note. Not all bootstrap samples were successful: CI based on 469 samples.

further examined by using confirmatory factor analysis employing bootstrap CI error calculation (samples = 1000) and found to be a good fit for the ASIST Study 3 sample data (CFI = 0.991, GFI = 0.996, RMSEA = 0.046, SRMR = 0.066, $\chi^2 = 239.391$, and df = 142, $p < .001$). See Table 3 and Table 4 below for additional model details.

Table 4. CFA Items R-Squared.

	R^2
Skill: LearnLayout	0.620
Skill: CommLocation	0.542
Skill: CoordTeam	0.518
Skill: TaskAwareness	0.535
Skill: LearnItems	0.479
Skill: TrackPathing	0.420
Skill: WASDcontrol	0.431
Skill: TrackLocation	0.569
LearnerConfidence	0.544
Frequency: VideoGames	0.878
Frequency: ComputerGames	0.661
Years: ComputerUse	0.399
Years: ComputerGames	0.470
Years: Non-ComputerGames	0.705
Frequency: TeamGames	0.613
Motivation	0.104
Competitive-Games	0.496
Perceived Proficiency	0.883
Perceived Experience	0.909

Discussion

This paper reports on a set of studies examining factors emerging from the Video Game Experience Measure (VGEM). First, findings from an exploratory factor analysis suggest a five-factor model, with the results of indicating that the correlation structure would be adequate for factor analyses. Next, a confirmatory factor analysis tested the five-factor model using a new set of subjects. Results of the confirmatory factor analysis found the five-factor model to be a good fit, and that the data supports the proposed factor structure. Findings show that the VGEM taps into general experience with respect to duration, frequency/intensity, and self-reported skill. These features of video game experience may transfer to novel task performance (Bendell et al., 2021a). With the VGEM, researchers can use its assessment to help account for the variance of prior experience in video games as it can influence the performance of participants in research and training.

Accounting for variance in task-related behaviors is important, and there are other practical considerations associated with video game experience that warrant attention from human subjects researchers, such as biases related to player motivation and study participation. When utilizing a gamified experimental task or recruiting participants through appealing to video game players, there may be confounding side-effects that artificially boost the power of participants' video game experience. Participant approaches to study measures and willingness to complete the measure may also be affected. However, accounting for the variance in participants through measuring prior experience can inform researchers of their study population that may impact results.

This work can be used to further research in the study of cognition and collaboration in a number of ways. Related to research in synthetic task environments designed for experimentation, which simulate complex operational environments, we provide support for a measure with a factor structure that is a good fit for describing player characteristics that impact performance. Accounting for variance allows researchers to better understand differences in task performance that are more likely due to video game experience. Further, by understanding participant characteristics, these kinds of measures can be used to create profiles of players (Bendell et al., 2021a), which can be used both in gamified research tasks to understand performance, as well as to provide a priori information to artificial intelligence that would aid the development of an Artificial Theory of Mind, allowing the AI to better interpret and predict human behaviors (Bendell et al, 2021b; Williams et al., 2022). Overall, the VGEM can help guide researcher decisions whenever gamified experimental tasks are used.

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