TYPE Original Research
PUBLISHED 28 November 2022
DOI 10.3389/feduc.2022.1062922



OPEN ACCESS

EDITED BY
Carmen Llorente Cejudo,
University of Seville,
Spain

REVIEWED BY
Dinny Devi Triana,
Jakarta State University,
Indonesia
Arturo Arrona-Palacios,
Harvard Medical School,
United States

*CORRESPONDENCE
Sumiyana Sumiyana
sumiyana@ugm.ac.id

†These authors have contributed equally to this work and share first authorship

SPECIALTY SECTION
This article was submitted to Digital Education, a section of the journal Frontiers in Education

RECEIVED 06 October 2022
ACCEPTED 10 November 2022
PUBLISHED 28 November 2022

CITATION
Sumiyana S, Fajri FA, Saputra MA and Hadi C (2022) Enhancing cognitive combat readiness: Gamers' Behaviours concentrating on convergent learning style, tacit-latent, and kinetic-active knowledge acquisitions. *Front. Educ.* 7:1062922. doi: 10.3389/feduc.2022.1062922



# Enhancing cognitive combat readiness: Gamers' Behaviours concentrating on convergent learning style, tacit-latent, and kinetic-active knowledge acquisitions

Sumiyana Sumiyana*†, Faridiah Aghadiati Fajri†, Muhammad Adlin Saputra† and Caraka Hadi†

Master of Science and Doctorate Programme, Faculty of Economics and Business Gadjah Mada University, Yogyakarta, Indonesia

This study investigates gamers' learning styles and knowledge acquisition behavioural patterns. It argues that gamers usually have different characteristics transforming themselves to gain distinctive competencies. In other words, this study mitigates gamers' mechanistically distinctive attitudes and behaviours, enhancing their cognitive combat readiness, that they are on convergent learning style, tacit-latent, and kinetic-active knowledge acquisitions. Methodologically, it uses a field-experimental design using the "Clash Royale" game. Then, this research measures playing performances by average decks' score, card collection, battle deck combinations, and the usage of gold and gems. Moreover, it collects gamer respondents using a purposive sampling method by identifying them on social media and then challenging them to play. This research finds that gamers acquire new knowledge to enhance their capabilities with convergent learning styles and familiarity with the tacit-latent and kinetic-active knowledge types. Thus, it demonstrates its attitude and behavioural validities because their inner motives construct themselves always to win the game matches genuinely. Hence, it explains that gamers generally are brilliant young individuals whose impact is to create their tactically contemporary style due to the learning cycle ending in that convergent style. Likewise, these gamers simultaneously seek flexibility to enhance the game kinetically or elastically. The authors reveal that gamers' mental models show their learning styles and knowledge acquisition behaviours explained by their strong personalities, such as curious, workaholic, prestigious, and hedonic emotions.

KEYWORDS

**learning style, knowledge acquisition, convergence, active, latent, kinetic, tacit**

## Introduction

This study investigates gamers' learning styles by comparing the convergent type to accommodative, divergent, and assimilative types. In addition, the authors simultaneously investigate gamers' knowledge acquisition focused on kinetic-active and tacit-latent models compared to actor-active and material-latent ones. Furthermore, the study connects gamers' learning styles and knowledge acquisition, constructing their specific behaviours (McCrow et al., 2014; Yousef, 2016; Hamdaoui et al., 2018). Developing this study's goal, the authors argue that gamers' personalities, like being curious, workaholics, and gaining prestige by dominating and winning matches, shape their cognition. Moreover, naturally dominant awareness, such as military troopers, affects their attitudes and behaviours in combat readiness (Yurechko, 1988; Griffith, 2002; Herspring, 2006). Meanwhile, this study proposes using cognitive combat readiness for gamer attitudes and behavioural characteristics. In brief, it argues that gamers emerge from all concepts or theories in their cognition, transforming to practical methods in finishing a match. On the other hand, gamers should always react and explore problem-solving efficiently with their cumulative knowledge. Thus, this study demonstrates that gamers' cognitive demands require them to be definite in their convergent learning styles and kinetic knowledge acquisition.

This study presents its novelties to answer the critical need of its investigation, arguing constructive contexts of gamers' attitudes and behavioural learning styles associated with their knowledge acquisition. Starting from the authors' explorative proposition, we captured that gamers' cognitive combat readiness is more likely equivalent to soldiers' combat readiness. However, we noted that gamers focus on their cognition only, and then we innovate the gamers' cognitive combat readiness. First, it argues that gamers' personality traits, such as military perspectives, are specific to combat readiness (Griffith, 2002; Strandenes et al., 2013; McCrow et al., 2014). It transforms this term into cognitive combat readiness for these gamers, meaning that gaming cognition is based on technical practises (Yurechko, 1988; Herspring, 2006; Tsarouhas and Makrygianni, 2017). Moreover, these gamers swiftly transform theories and concepts into technical practises implemented in problem-solving (Sánchez and Olivares, 2011; Sahasrabudhe and Kanungo, 2014; Dantas and Cunha, 2020). Thus, gamers internalise learning styles and knowledge acquisition, gaining distinctive attitudes and behaviours in convergent, kinetic-active, and tacit-latent contexts. Moreover, this study demonstrates that other people cannot adopt these gamers' learning styles and knowledge acquisition due to a lack of curiosity, a workaholic, and a sense of prestigious pressure. It also explains that cognitive combat readiness gamers gain highly coordinated communication and reduce asymmetric information amongst their partners.

This second novelty is this study's gamer-focused argumentation regarding convergent learning styles and concentrated on kinetic-knowledge acquisition. This research explains that gamers unconsciously adopt convergent learning styles due to no long durations when executing their decisions. In other words, gamers should condition their cognition on decisive punctuality (Manolis et al., 2013; Sahasrabudhe and Kanungo, 2014; García-Campos et al., 2020). With this loose timeliness in decision-making, the gamers will not win the matches. Then, they should emerge with their unique concepts and theories in technical and practical problem-solving. On the other side, this study explains that gamers face a multi-dimensional environment, affecting their proper response. The authors argue that gamers should consider three dimensions in thinking-feeling, judging-perceiving, and intuitive-sensing (Nacke et al., 2014; Dale and Green, 2017; Kamal and Radhakrishnan, 2019). The environment stimulates gamers to organise and adapt their cognition (Sadler-Smith and Riding, 1999; Goulding and Syed-Khuzzan, 2014; Seo et al., 2021) matches. This research explains that gamers consider multi-dimensional inputs processed in their comprehension to emerge a unique decision, formulating convergent learning styles. Furthermore, gamers' endowment concepts and theories, including previous experiential learning, made them flexible in switching their reactive, and newly explorative cognition (Dodd et al., 2005; Fox et al., 2018; Van der Lingen et al., 2020). When gamers do not have concepts, theories, and experiential values, they swiftly search for referential decision-making. Thus, they absorb in an elastically cognitive way, fashioned in tacit-latent, and kinetic-active knowledge acquisition.

Third, this research presents a novel argument in its methodology, elaborating on these gamers' attitudes and behaviours. Furthermore, it places gamers in convergent learning styles as the dominant one (Müller-Wienbergen et al., 2011; Hamdaoui et al., 2018; Hong et al., 2021) and simultaneously in kinetic-active and tacit-latent knowledge acquisitions (Linde, 2001; Zebal et al., 2019; Johannessen, 2021). Firstly, this research examines the cognitively dominant roles of gamers' convergent learning styles. Next, it investigates gamers' dominance in kinetic-active and tacit-latent knowledge acquisitions. Then, this research associates the gamers' learning styles and knowledge acquisition (Banner and Rayner, 2000; Strayer and Beitz, 2010; Hamdaoui et al., 2018); this relationship has the highest value compared to the others amongst those combining those styles and acquisitions. Secondly, this research examines the dominantly causal association higher than other combining ones. Finally, when the first and second stepped tests are valid, it shows the robustness of gamers' learning styles and knowledge acquisition and whether they have distinctive behaviours.

This study uses three clustered theories to explain the gamers' learning styles and knowledge acquisition. The first clustered theory pertains to accommodative, convergent, divergent, and assimilative learning styles (Papa et al., 2017; Hamdaoui et al., 2018; Hong et al., 2021). Moreover, this study focuses on gamers' divergent learning styles due to their personalities. The second cluster is knowledge acquisition explaining methodological choices of gamers' behaviours in enhancing their capabilities and competencies (Hung and Lin, 2015; Kamal and Radhakrishnan, 2019; Chung and Jung, 2020). In comprehending gamers' characteristics, this study argues that gamers probably engage in kinetic-active and tacit-latent learning because of their cognitive-behavioural suitability for the technological environment. Finally, the remaining cluster pertains to combat readiness viewed from the military approach (Yurechko, 1988; Rosen and Martin, 1998; Hanson, 2003; Erden et al., 2008). However, this study transforms this theory, embedding the cognitive combat readiness for gamers' attitudes and behaviours. As a result, it comprehends how gamers exhibit convergent learning styles, and kinetic-active and tacit-latent knowledge acquisitions due to the emergence of cognitive combat readiness. Moreover, it demonstrates that, cognitively, gamers should be combat-ready when they genuinely play a match to win.

This study contributes to the literature on practical and theoretical learning styles and knowledge acquisition, probably impacting academic performance. The first contribution is that combined convergent learning styles and kinetic-active knowledge acquisition present unique learning systems. It is also valid for the combined convergent learning styles and tacit-latent knowledge acquisition. Consequently, this study argues that learning systems assist students with convergent and kinetic-active or tacit-latent learning. Moreover, this combination will support academic and vocational learning emphasising practical jobs (Zebal et al., 2019; Jayalath and Esichaikul, 2020; Lei et al., 2021). Finally, this study comprehends that learning supremacy leads to this combination due to students' emerging reactive and explorative cognition (Jurado and Meza, 2017; Ewell et al., 2018; Khanmurzina et al., 2020). Hence, students can also enhance their competencies in decision-making when they face problematic situations and short-time pressures.

The second contribution relates to constructive behaviours for educator awareness to create students' cognitive combat readiness. Other perspectives are the enhancement of their cognitive combat readiness, making students always masculine and eager to accomplish their tasks (Johnson, 2010; Sanjamsai and Phukao, 2018; Khanmurzina et al., 2020). Then, educators have the responsibility to increase students' cognitive combat readiness. Moreover, they accentuate dimensions of combat readiness internalised to students' cognition, such as knowledge accumulation, practical transformation, problem-solving, etc. Conversely, this signals the need for resilient methods for students to engage their cognitive readiness and achieve a student-centred learning system (Strandenes et al., 2013; Tsarouhas and Makrygianni, 2017; Dantas and Cunha, 2020). Finally, this study demonstrates students' achievement of an efficient learning system due to their signified engagement. Hence, this cognitive combat readiness aligns with the conditionalism of student cognition in gaining competitive performances.

The remaining sections will discuss the theoretical framework to explain gamers learning styles and knowledge acquisition. The third section deals with research methods for learning style measurements and experimental games to acquire gamers' knowledge. Statistical results and findings are presented in section four. Finally, the study ends with conclusions and future research suggestions.

## Literature review and hypotheses development

### Learning styles

This study posits Keefe (1979) to explain that learning styles are individual cognitive and affective behaviours in interacting and reacting to environments. Griggs and Dunn (1984) differentiate between unique visual, auditory, and kinesthetic learning styles. Meanwhile, Allinson and Hayes (1996), Willingham et al. (2015) explain that learning styles based on individuals' preferences involve cognitive processes to differentiate between their intuitive and analytical thinking. Additionally, Abel et al. (2018), Alexander (2020), Olanipekun et al. (2020), Van der Lingen et al. (2020) categorise learning styles into; (1) accommodative; (2) convergent; (3) divergent; (4) assimilative. Most extant studies explain that accommodative learning styles acquire knowledge through deepened experiences from others. The individual with accommodative learning prefers to use intuitive techniques than critical logic. Convergent learning styles acquire knowledge using their endowed concepts and theories in their cognition. These convergent styles are also highlighted with their swifted transformation from concepts and theories to practical and technical methods. Divergent learning styles search knowledge visually, auditory and kinetically. The last is assimilative learning styles that acquire knowledge only through practising directly. Furthermore, this study considers to these extant research, concerning individuals' learning styles. However, those extant research did not relate these styles with gamers' cognitive behaviours, characterised by genuine combat readiness.

With four typological methods from previous research, this study argues that individuals search for the most suitable methods to achieve their performances. Then, it considers literature gaps in most extant research, specifically not discussing gamers' learning styles. Moreover, it investigates the relationship between the gamers' learning styles with specific behaviours and their effortful combat readiness. It explains that gamers receive knowledge, becoming a practical and technical tool to win a match. It infers that gamers simultaneously use visual, auditory and kinesthetic senses (Jurado and Meza, 2017; Hamdaoui et al., 2018; Hilvert-Bruce and Neill, 2020) to simulate all menus, features, elements and movements as if they are in the real world. On the other hand, this study uses extended learning styles and highlights that gamers lead to a convergent one (Manolis et al., 2013; Jurado and Meza, 2017; Hong et al., 2021) due to expertise in actualising concepts and theories transforming to be technical and practical.

This research identifies gamers' learning styles to capture their cognitive and affective behaviours. It posits Al Shaikh et al. (2019), García-Campos et al. (2020), and Kolb and Kolb (2005) to explain gamers' learning styles associating knowledge, capabilities and attitudes. On the other hand, it posits Andreou et al. (2014), Dantas and Cunha (2020), and Garner (2000) argue that individuals' learning styles do not only restrict gaining answers but also identifying processes. Therefore, this research infers that learning style is a method for individuals to interact with others through their cognitions, affections, physics and environments (Li and Wang, 2013; Alexander, 2020; Olanipekun et al., 2020). Thus, it considers that gamers' learning styles focus on innovativeness to create and develop critical reasoning and problem-solving. Finally, the authors believe that gamers' learning styles will be convergent due to motives of expertise enhancement to win the match. In other words, gamers learn new concepts and theories that make them cognitively flexible. Therefore, gamers enhance their capabilities and competencies from constitutive dexterity skills, memory, mental strength, collective knowledge, and mechanical flows.

## Knowledge acquisition

This study posits Cegarra-Navarro et al. (2019), Jayalath and Esichaikul (2020), and Olanipekun et al. (2020) to explain that individuals acquire knowledge through latent knowledge: tacit or material, or active: actor or kinetic, and cross-cutting catalyst epiphany (CCCE). Tacit-latent acquisition refers to acquiring knowledge through repetitive and directive practises. Material-latent acquisition acquires knowledge through media attributing with referential contents of structures, procedures, systems, etc. On the other hand, individuals who collect knowledge actively use their roles as actors, understanding through interfaces and rules. Thus, actor-active knowledge acquisitions refer to traditional teaching-studying methods. Kinetic-active explains that an individual pursues knowledge in reactive and explorative approaches through methodological flexibilities. The last is CCCE acquisition, in which individuals collect knowledge as it emerges unpredictably and immediately at random. The authors note that this CCCE is not involved in this study due to rare individual usage (Dufwenberg et al., 2010; Gneezy et al., 2010; Alexander, 2020). Therefore, considering all these extant research, this study infers that individuals acquire knowledge through two clustered acquisition types (Breen and Lindsay, 1999; McCrow et al., 2014; Alberti and Pizzurno, 2015; Visser-Wijnveen et al., 2016; Hamdaoui et al., 2018): latent or active. Hence, individuals search for knowledge through these possibilities aforementioned by these extant research, except for gamers with an unidentified acquisition. In addition, we believe that gamers acquire knowledge differently, fitting with their cognitive characteristics of combat eagerness. Thus, it arranges gamers' acquisition of knowledge that could be four possibilities: tacit-latent and actor-active; tacit-latent and kinetic-active; material-latent and actor-active; material-latent and kinetic-active.

This study argues that gamers' attitudes and behaviours are distinctive compared to others. Therefore, the authors believe that gamers have unique personalities in acquiring knowledge in tacit-latent (Howells, 1996; Erden et al., 2008; Lei et al., 2021) and kinetic-active types (Linde, 2001; Arthurs, 2007; Liew et al., 2021). The authors support this focused knowledge acquisition for gamers, a natural characteristic. Moreover, they pursue tacit-latent knowledge internalised into their cognition, indicating reflective behaviours (Hung and Lin, 2015; Seo et al., 2021; Thomas and Gupta, 2021). Comprehensively, gamers concentrating on kinetic-active knowledge acquisitions always enhance their expert skills to master their capabilities and competencies (Hung et al., 2015; Giampaoli et al., 2017; Jung J., 2020; Thongmak, 2020). Moreover, they improve their gamification mastery because of the need for repetitive requirements and dynamic flexibility for problem-solving. Finally, this study demonstrates gamers' strong personality traits of being curious, workaholic, prestigious, and hedonic to win the game, constructing themselves to focus on tacit-latent and kinetic-active knowledge acquisition.

## Gamer behaviours and cognitively combat readiness

Gamers' behaviours are always associated with addictive enjoyment and hedonic personalities. This study also explains that people's stigma for being addicted to internet gamers and e-sport players does not exhibit a social distance from gamblers (Griffith, 2002; Johnson, 2010; Peter et al., 2019). The authors consider gamers' changing social behaviours and practises as an integral part of lifestyles in communication in their environments (Silva et al., 2015; Zimmermann et al., 2018; Bustamante et al., 2020; Khanmurzina et al., 2020). On the other hand, game types impact behavioural aspects due to conditional pressures, fatigue, endurance, etc. This study considers Chen et al. (2016), Drachen et al. (2014), Fox et al. (2018), Garcia-Manero et al. (2016) and clusters game types affecting gamers' behaviours, such as full game (highly frequent touches), hardcore game (acting as shooters and sports players), casual game (music, social aspects, and moderately thinking), and others (no preferences). Therefore, the authors infer that behavioural characteristics imply gamers' cognition because of frequent repetitions, intensive broadening of knowledge, proper communication without asymmetry, etc. For example, this study posits Ewell et al. (2018), Kamal and Radhakrishnan (2019), Li and Wang (2013), and Sanjamsai and Phukao (2018) to explain how gamers play for long durations to signify their imaginary thoughts, preparing multiple strategies for competitions.

This study posits Bustamante et al. (2020), Garcia-Manero et al. (2016), Jung C. W. (2020), Sumiyana et al. (2022), Teng (2008), who find that gamers' social communities affect their social awareness of always existing professionally. Furthermore, this study considers gamers' behaviours characterised by social aspects, such as communicating, collaborating, coordinating, competing, etc. It also highlights that gamers develop relational cohesiveness, building team loyalty (Sumino and Harada, 2004; Mandryk and Birk, 2017; Huang et al., 2021). This extant research investigated the effectiveness of gamers' social communities, improving sound mentality or depressing it (Silva et al., 2015; Király and Demetrovics, 2017; Hilvert-Bruce and Neill, 2020; Rozgonjuk et al., 2021). Therefore, this study infers that game types and social communities construct gamers' behaviours, especially cyber aggressors and distractor characters.

Inferencing gamers as aggressors and distractors, this study associates gamers' learning styles and knowledge acquisition with combat readiness, such as military troopers. Combat readiness measures an army soldier preparing for combat (Rosen and Martin, 1998; Hanson, 2003; Tyler et al., 2012; Laanepere and Kasearu, 2021). Moreover, the authors highlight combat readiness equipped with mentality, weapons, technology, radio communication, etc. This study borrows the combat readiness measurement from the military, transforming it into gamers' behaviours. However, this measurement changed to cognitive combat readiness because gamers did not require physical fitness like soldiers. This study argues that gamers' cognitive combat readiness captures their learning styles and knowledge acquisition from various perspectives (Cegarra-Navarro et al., 2019; Alexander, 2020; Toth et al., 2020). It explains gamers' multi-dimensional conditions when they play a match against others. They should always utilise their conceptual and theoretical endowments to win the matches (Nacke et al., 2014; Dale and Green, 2017; Sumiyana et al., 2022).

On the other hand, this study supports the constructive measurement of cognitive combat readiness because gamers situate themselves in curiosity, excitement, anxiety, etc. Moreover, gamers should control their cognition to be innovative to win the game match. Gamers use innovativeness to actualise their cumulative concepts swiftly, theories and experiential values to challenge and attack their enemies in the gams (Hartman et al., 2006; Ladeira et al., 2016; Thongmak, 2020). In other words, gamers always search for the subsequent knowledge needed to master their cognitive combat readiness and win competitions (Yurechko, 1988; McAllister et al., 2013; Alexander, 2020). Furthermore, the study summarises that gamers' behaviours require them to accumulate knowledge, enhance innovativeness and solicit mastery. Finally, gamers should align their learning styles and knowledge acquisitions to control their talent to succeed in winning matches.

## Hypotheses development

This study argues that gamers' convergent learning styles generally use concepts, theories and experiential learning values to be more adaptive and innovative due to game competitions. Elements are abstract conceptualisation and active experimentation, and gamers can accumulate theoretical and practical knowledge, actualising the match (Manolis et al., 2013; Goulding and Syed-Khuzzan, 2014; Hamdaoui et al., 2018). Moreover, gamers having both elements could enhance their cognitive combat readiness due to fundamentally acquiring that knowledge to be practised in the matches to win the competition (Herspring, 2006; Tyler et al., 2012; Khenissi et al., 2016). On the other hand, gamers facing various challenges in every match must be innovative to win the competition (Ladeira et al., 2016; Alexander, 2020; Thongmak, 2020). Furthermore, the authors demonstrate that these elements of abstract conceptualisation and active experimentation direct gamers' convergent learning styles to mastering their cognitive combat readiness. Thus, gamers are always charged with personal innovativeness to win the match over other gamers. In other words, they cope with avoiding match losses with their learning styles convergently. Then, they can shorten the time needed to rotate their experiential learning values compared to other techniques. Therefore, this study formulates hypothesis H1 below.

> *H1*: Gamers' convergent learning styles gaining their cognitive combat readiness are higher than others.

Naturally, gamers always accumulate tacit-latent knowledge aligning with their long-run capacities and demands. When gamers have gained tacit-latent knowledge, they can actualise their expertise, skill and competencies to win each game match. The same applies to kinetic-active knowledge acquisition (Gray, 2001; Kamal and Radhakrishnan, 2019; Wang et al., 2020; Lei et al., 2021). In other words, gamers' tacit-latent knowledge enhances their cognitive combat readiness (Griffith, 2006; Herspring, 2006; Tsarouhas and Makrygianni, 2017). Moreover, gamers always face various situations ending with the requirement to conduct problem-solving swiftly and innovatively. This study explains that gamers' tacit-latent knowledge could expose their reflective skills to higher combat readiness than material-latent ones (Park and Moon, 2003; Dodd et al., 2005; Strandenes et al., 2013; Toth et al., 2020; Seo et al., 2021). On the other hand, gamers' kinetic-active knowledge can adapt to challenging competitions. Moreover, gamers with highly accumulated tacit-latent and kinetic-active knowledge acquisitions can easily comprehend their cognitive combat readiness in each match because of enhanced adaptive behaviours (Griffith, 2006; Goulding and Syed-Khuzzan, 2014; Jayalath and Esichaikul, 2020). Therefore, this study explains that gamers orienting on the accumulated tacit-latent and kinetic-active knowledge acquisitions gain their cognitive combat readiness compared to the material and actor-active ones. In addition, the authors argue that these knowledge acquisitions are the most efficient approaches for gamers because of constructing their cognitive flexibilities. Moreover, these acquisitions structuralise gamers achieving more adaptive cognition facing dynamic situations with skill and expertise endowments. Thus, it constructs hypotheses H2 and H3 below.

> *H2*: Gamers' tacit-latent knowledge acquisitions gaining their cognitive combat readiness are higher than material-latent ones.

> *H3*: Gamers' kinetic-active knowledge acquisitions gaining their cognitive combat readiness are higher than actor-active ones.

This study proposes that formal learning styles and knowledge acquisition will quickly lead to mastery of capabilities and competencies. Therefore, gamers' convergent learning styles develop their endowed concepts, theories and experiential values to repetitively practise in the next game in a competition (Jurado and Meza, 2017; Papa et al., 2017; Hong et al., 2021). Simultaneously, gamers with convergent styles train themselves to improve their combat readiness Johnson (2010), Rosen and Martin (1998), Tsarouhas and Makrygianni (2017) through heavy preparation and calculation of dynamic situations to stabilise the match-winning in the game. Gamers are naturally interested in technical and methodological practises, mastering their cumulative knowledge implemented in subsequent competitions. Furthermore, this study acknowledges that gamers' convergent learning styles continue to acquire tacit-latent knowledge (Howells, 1996; Zebal et al., 2019; Lei et al., 2021) and kinetic-active ones (Griffith, 2002; Hamdaoui et al., 2018; Jayalath and Esichaikul, 2020). For example, they would no longer look at the keyboard to run the game competition. Then, gamers' knowledge acquisition enhances their cognitive combat readiness, practising in the tournaments. In brief, this study explains that compounds of convergent learning styles and tacit-latent or kinetic-active knowledge acquisitions could lift gamers' expertise skills and competencies. Moreover, the authors argue that gamers always enhance their situational competition fits, inducing multi-features, multi-tools, and timeliness execution into their cognition. Finally, gamers always search for exceptional skills and expertise that can be delayed any longer. Therefore, it formulates hypotheses H4 and H5 below.

> *H4*: Gamers' convergent learning styles and tacit knowledge acquisitions gaining their cognitive combat readiness are higher than other and material-latent ones.
>
> *H5*: Gamers' convergent learning styles and kinetic-active knowledge acquisitions gaining their cognitive combat readiness are higher than other styles and actor-active ones.

# Research method

## Research design and respondent collections

This research design uses respondents who are gamers categorised into each learning style. In addition, they are also either engaged in active knowledge acquisitions, such as active (actor or kinetic) or latent ones (tacit or material). In other words, a respondent has a single learning style and an active knowledge acquisition of actor or kinetic, or a latent one that is tacit or material. Furthermore, this study collects respondents for each cell numbering about 30 gamers. Thus, it manages all the respondents, who number about 240 gamers, because they have acquired active and latent types of knowledge. On the other hand, this study has a field-experimental research design with the matrices of $4 \times 2$ for learning styles and active knowledge acquisitions and $4 \times 2$ for latent ones. In addition, this research uses two sequential data collections in the field experiment. The first sequence is that the authors identify gamers by social media. Furthermore, the second one is that we ascertain these gamers with the year of experience. Moreover, we challenge these gamers to match with us with Clash Royale (Table 1).

This research collects the data using random purposive sampling. It frames collected homogeneous respondents with these criteria: (1) having played games for more than a year; (2) having competed in at least one tournament; and (3) playing for more than 3 h daily. The criteria intend to minimise confounding bias, used to keep causality. This study identifies gamers on social media, and the researchers challenge them to play this experimental game. In addition, questionnaires are sent to these gamers to fill in. Furthermore, this study uses these questionnaires to measure gamers' learning styles and knowledge acquisition. Finally, the research treats gamers with specific manipulated measurements for their cognitive combat readiness developed and conducted by the researchers. Additionally, the authors challenge the participants to be reactive, innovative, aggressive, and explorative in these matches. In addition, the researchers score gamers' cognitive combat readiness using an ideal score depending on the game's itemising.

## Variable measurements and recorded manipulation

This study used extant research on learning styles, knowledge acquisition and combat readiness. The researchers first sent a questionnaire to measure gamers' learning styles and knowledge acquisition in the data collection process presented in Appendix A. Moreover, in this data collection process, the researchers manually record an ideal deck's average score achieved by the gamers to measure their cognitive combat readiness. This study uses the specified "Clash Royale" game in this context. Thus,

TABLE 1 Research design.

| | | Knowledge acquisitions | | | |
|---|---|---|---|---|---|
| | | Active | | Latent | |
| | | Actor | Kinetic | Tacit | Material |
| Learning Styles | Accommodative | Cell-A | Cell-E | Cell-1 | Cell-5 |
| | Convergent | Cell-B | Cell-F | Cell-2 | Cell-6 |
| | Divergent | Cell-C | Cell-G | Cell-3 | Cell-7 |
| | Assimilative | Cell-D | Cell-H | Cell-4 | Cell-8 |

 10.3389/feduc.2022.1062922

the authors chose this game for its relevancy to gamers' confidence in the complex featured measures, the many options to implement strategies, game-match readiness in the short duration, personal innovativeness, and multiple flows of cognitive states. Moreover, this study fits this game type by using various decks to measure cognitive combat readiness. This recording is the manipulative treatments conducted by researchers. This average score form that measures gamers' mental combat readiness is in Appendix B.

## Statistical tests

This study examines all hypotheses by comparing cells according to the hypothetical contents. It uses mean comparison tests of ANOVA independent sample *t*-test. For example, testing hypothesis H1 identifies gamers' convergent learning styles gaining a cognitive combat readiness higher than other learning styles. It compares the Cell-B and F higher than other cells in active knowledge acquisitions. In latent knowledge acquisitions, it reaches Cell-2 and Cell-6 higher than other cells. This study presents these closed-comparative equations in Models (1)-(5) for shortage statements of all hypotheses. Finally, it supports the ease of readability for these hypotheses tests by presenting comparative equations below. Meanwhile, this study uses the ANOVA independent *t*-test, and when it fails to diagnose these comparisons, it transforms into a statistical comparative-contrast analysis.

$$\begin{aligned}\mathbf{H1}: &\text{Cell} - \text{B}; \text{F} > \text{Cell} - \text{A}; \text{E}; \text{C}; \text{G}; \text{D} \ \& \ \text{H, and} \\ &\text{Cell} - 2; 6 > \text{Cell} - 1; 5; 3; 7; 4 \ \& \ 8\end{aligned} \tag{1}$$

$$\mathbf{H2}: \text{Cell} - 1; 2; 3; \&4 > \text{Cell} - 5; 6; 7 \ \& \ 8 \tag{2}$$

$$\mathbf{H3}: \text{Cell} - \text{E}; \text{F}; \text{G}; \&\text{H} > \text{Cell} - \text{A}; \text{B}; \text{C}; \&\text{D} \tag{3}$$

$$\begin{aligned}&\mathbf{H4}: \text{Cell} - 2 > \text{Cell} - 5; \text{Cell} - 2 > \text{Cell} - 7; \\ &\text{Cell} - 2 > \text{Cell} - 8; \text{Cell} - 2 > \text{Cell} - 5; 7; \&8\end{aligned} \tag{4}$$

$$\begin{aligned}&\mathbf{H5}: \text{Cell} - \text{F} > \text{Cell} - \text{A}; \text{Cell} - \text{F} > \text{Cell} - \text{C}; \\ &\text{Cell} - \text{F} > \text{Cell} - \text{D}; \text{Cell} - \text{F} > \text{Cell} - \text{A}; \text{C}; \&\text{D}\end{aligned} \tag{5}$$

## Statistical results

This study collects participants in two steps. The first step identifies gamers through social media, marking them as real players. Then, the authors ask these identified gamers to answer a questionnaire using Google Forms. In the second step, the authors challenge these participants to a match in "Clash Royale" with others or the authors in an appointed public area. Moreover, this research took 7 months to collect data samples, resulting in 132 gamers. It also deleted nine participants who did not complete the gaming stages, meaning there were 123 in the final sample. Then, overall data show that 79 participants are male (64.22%), with game expertise, 78 have more than 1 year of experience (63.41%), and 90 have been involved in at least one tournament (73.17%). Thus, this study infers that the data collected are from experienced gamers presented in Table 2.

Table 3 presents the number of participants, mean, and standard deviation of respondents' cognitive combat readiness occupying each cell. This research formerly conducted a pilot test to validate the questionary. After collecting the first eight participants, we believed no material doubts, and then we continued to collect the following participants. Furthermore, participants with accommodative-actor have the lowest mean value of 3.139. Conversely, the highest mean value of 4.586 is participants concentrating on the convergent-kinetic. Furthermore, the authors infer that each data item typically deviates from the mean values, reflecting central homogeneity. Thus, this study concludes that each data cell is typically distributed, which could be compared parametrically.

This study has designed validity and reliability tests for the 123 respondents. Table 4 shows the test results for each cell. First, Panel-A shows that the factor loading value of each item is more than 0.5, gaining convergent validity. In addition, the Corrected-Item-Total Correlation value for each item question is more than 0.5 and never higher than these factor loading values, indicating the discriminant validity. Then, Cronbach's alpha value shows that each item value is more than 0.8 and is not higher than the compounded value. Thus, this study infers that each variable achieves high reliability. In addition, the study develops specific measurements for material knowledge acquisition employing scoring systems equivalent to a 5-points Likert scale. Specifically, Panel-B shows that the 10-item questions are material-latent types. Each correct answer is valued at 0.50, and 0.00 for the wrong answer, reaching a maximum score of 5.00. Therefore, the authors conclude that each item score gained a fixed point.

TABLE 2 Demographic data.

| Learning styles | Frequency | | | | | | |
|---|---|---|---|---|---|---|---|
| | *n* | Gender | | Gamer's experiences | | Tournament | |
| | | Male | Female | <1-year | >1-year | Yes | No |
| Accommodative | 31 | 21 | 10 | 14 | 17 | 20 | 11 |
| Convergent | 37 | 25 | 12 | 5 | 32 | 34 | 3 |
| Divergent | 25 | 17 | 8 | 11 | 14 | 17 | 8 |
| Assimilative | 30 | 16 | 14 | 15 | 15 | 19 | 11 |
| Total | 123 | 79 | 44 | 45 | 78 | 90 | 33 |

TABLE 3 Descriptive statistics.

| x: cognitively combat readiness | | Knowledge acquisitions | | | |
|---|---|---|---|---|---|
| | | Active | | Latent | |
| | | n: 246 | | 246 | |
| | | $\bar{x}$ : 3.857 | | 3.928 | |
| | | SD: 0.8673 | | 0.9070 | |
| | | **Actor** | **Kinetic** | **Tacit** | **Material** |
| | | 123 | 123 | 123 | 123 |
| | | 3.628 | 4.087 | 4.111 | 3.744 |
| | | 0.9635 | 0.6901 | 0.7922 | 0.9780 |
| Learning | **Accommodative** | | | | |
| Styles | n: 124; | 31 | 31 | 31 | 31 |
| | $\bar{x}$ : 3.841; | 3.139 | 4.054 | 3.849 | 3.613 |
| | SD: 0.9089 | 0.8147 | 0.5715 | 1.0322 | 0.9102 |
| | **Convergent** | | | | |
| | 148 | 37 | 37 | 37 | 37 |
| | 4.462 | 4.488 | 4.586 | 4.477 | 4,297 |
| | 0.5296 | 0.4695 | 0.5048 | 0.5960 | 0.5199 |
| | **Divergent** | | | | |
| | 100 | 25 | 25 | 25 | 25 |
| | 3.563 | 3.460 | 3.887 | 3.907 | 3.000 |
| | 0.9701 | 0.9660 | 0.6955 | 0.6420 | 1.2162 |
| | **Assimilative** | | | | |
| | 120 | 30 | 30 | 30 | 30 |
| | 3.700 | 3.213 | 3.806 | 3.967 | 3.817 |
| | 0.8268 | 0.8776 | 0.7156 | 0.6800 | 0.8457 |

Table 5 is the continued process of comparing the mean values of the collected data from participants in Table 3. Then, we compare amongst cells resulting mean differences, *t*-values and significances with asterisk signs. Furthermore, Table 5 exhibits the statistical results for all mean comparison hypotheses, revealing the overall supported views in Models (1)–(5). Specifically, hypothesis H1 proposed that active and latent knowledge acquisition mastered by convergent gamers' learning styles have the highest combat readiness compared to others. The statistical results support hypothesis H1 with a mean difference of 0.7991 and a *t*-value of 7.449, which is a significant 1.00%. Likewise, hypothesis H2 is supported, meaning that gamers' combat readiness dominated the knowledge acquisition of tacit-latent and kinetic-active learning compared to others, with a mean difference of 0.3672 and a *t*-value of 3.924. This hypothesis was statistically significant at 1.00%. Finally, supporting hypothesis H3, statistical results at a significance level of 1.00% confirmed that kinetic-active gamers have higher combat readiness than kinetic-actor with a 0.4587 mean different value and 7.356 *t*-value.

The statistical results show a mean value of 4.477 and a standard deviation of 0.596 from the testing of hypothesis H4. Overall, the mean difference, *t*-value and significance were 0.4587, 7.356, and 1.00%, respectively. Therefore, this statistical result supports hypothesis H4, arguing that convergent-tacit gamers demonstrate the highest combat readiness compared to those material-others.

TABLE 4 Validity and reliability.

**Panel-A**

| Variables | Item | Factor loading | Corrected-item-total correlation | Cronbach's alpha | |
|---|---|---|---|---|---|
| *Accommodative* | | | | | |
| Actor | Act1 | 0.801 | 0.760 | 0.928 | 0.934 |
| | Act2 | 0.627 | 0.599 | 0.933 | |
| | Act3 | 0.822 | 0.768 | 0.928 | |
| | Act4 | 0.632 | 0.587 | 0.932 | |
| | Act5 | 0.906 | 0.875 | 0.924 | |
| | Act6 | 0.580 | 0.436 | 0.935 | |
| | Act7 | 0.838 | 0.814 | 0.926 | |
| | Act8 | 0.679 | 0.623 | 0.933 | |
| | Act9 | 0.757 | 0.730 | 0.929 | |
| | Act10 | 0.680 | 0.650 | 0.931 | |
| | Act11 | 0.667 | 0.599 | 0.932 | |
| | Act12 | 0.782 | 0.715 | 0.929 | |
| | Act13 | 0.615 | 0.559 | 0.933 | |
| | Act14 | 0.863 | 0.829 | 0.926 | |
| | Act15 | 0.657 | 0.636 | 0.932 | |
| | Act16 | 0.566 | 0.487 | 0.934 | |
| Kinetic | Kin1 | 0.943 | 0.926 | 0.958 | 0.964 |
| | Kin2 | 0.788 | 0.754 | 0.963 | |
| | Kin3 | 0.836 | 0.799 | 0.962 | |
| | Kin4 | 0.880 | 0.847 | 0.960 | |
| | Kin5 | 0.826 | 0.791 | 0.962 | |
| | Kin6 | 0.850 | 0.813 | 0.961 | |
| | Kin7 | 0.958 | 0.945 | 0.958 | |
| | Kin8 | 0.806 | 0.769 | 0.963 | |
| | Kin9 | 0.903 | 0.880 | 0.960 | |
| | Kin10 | 0.873 | 0.850 | 0.960 | |
| | Kin11 | 0.783 | 0.739 | 0.964 | |
| | Kin12 | 0.764 | 0.730 | 0.963 | |
| *Convergent* | | | | | |
| Actor | Act1 | 0.897 | 0.875 | 0.966 | 0.969 |
| | Act2 | 0.884 | 0.861 | 0.967 | |
| | Act3 | 0.910 | 0.893 | 0.966 | |
| | Act4 | 0.883 | 0.856 | 0.967 | |
| | Act5 | 0.896 | 0.877 | 0.966 | |
| | Act6 | 0.913 | 0.891 | 0.966 | |
| | Act7 | 0.894 | 0.882 | 0.966 | |
| | Act8 | 0.861 | 0.835 | 0.967 | |
| | Act9 | 0.766 | 0.733 | 0.969 | |
| | Act10 | 0.781 | 0.752 | 0.968 | |
| | Act11 | 0.850 | 0.824 | 0.967 | |
| | Act12 | 0.876 | 0.849 | 0.967 | |
| | Act13 | 0.763 | 0.730 | 0.969 | |
| | Act14 | 0.902 | 0.879 | 0.966 | |
| | Act15 | 0.886 | 0.869 | 0.966 | |
| | Act16 | 0.478 | 0.444 | 0.975 | |

*(Continued)*

TABLE 4 (Continued)

| Panel-A | | | | | |
|---|---|---|---|---|---|
| **Variables** | **Item** | **Factor loading** | **Corrected-item-total correlation** | **Cronbach's alpha** | |
| Kinetic | Kin1 | 0.763 | 0.698 | 0.913 | 0.920 |
| | Kin2 | 0.764 | 0.715 | 0.912 | |
| | Kin3 | 0.821 | 0.773 | 0.910 | |
| | Kin4 | 0.800 | 0.747 | 0.911 | |
| | Kin5 | 0.766 | 0.707 | 0.912 | |
| | Kin6 | 0.571 | 0.507 | 0.922 | |
| | Kin7 | 0.539 | 0.467 | 0.924 | |
| | Kin8 | 0.816 | 0.768 | 0.909 | |
| | Kin9 | 0.790 | 0.732 | 0.911 | |
| | Kin10 | 0.545 | 0.480 | 0.922 | |
| | Kin11 | 0.881 | 0.830 | 0.906 | |
| | Kin12 | 0.808 | 0.747 | 0.911 | |
| *Divergent* | | | | | |
| Tacit | Tac1 | 0.832 | 0.655 | 0.896 | 0.856 |
| | Tac2 | 0.932 | 0.816 | 0.727 | |
| | Tac3 | 0.904 | 0.752 | 0.783 | |
| *Assimilative* | | | | | |
| Tacit | Tac1 | 0.897 | 0.766 | 0.882 | 0.898 |
| | Tac2 | 0.880 | 0.741 | 0.905 | |
| | Tac3 | 0.959 | 0.895 | 0.769 | |
| **Panel-B** | | | | | |
| | **n** | **Item** | **Scoring** | **Total** | |
| Material-divergent and assimilative | 55 | 10 | 0.5 | 5 | |

Furthermore, hypothesis H5 in convergent-kinetic learning shows a mean value of 4.622 and a standard deviation of 0.285. This mean difference value is 1.3276, and the $t$-value of 8.558 with a 1.00% significance level, demonstrating that convergent-kinetic is higher than those actor-others. In the participants' field experiment, this study presents statistically robust results. It powerfully demonstrates that convergent-kinetic gamers have the highest combat readiness amongst those actor-others in mastering their knowledge acquisition. Thus, hypothesis H5 is supported twice.

## Discussion and findings

This research investigates gamer behaviours in acquiring knowledge through convergent and tacit-latent or kinetic-active learning styles. It demonstrates the specified gamer behaviours in this style and acquisition measuring using cognitive combat readiness. This study's statistical tests show high validity that gamers improve their knowledge through convergent techniques. Moreover, this research recognises that gamer behaviours are laid on the convergent type because they are people with excellent intellectualism. Therefore, it highlights the gamer's reliance on personal innovativeness completed by cognitively dynamic flexibilities (Griggs and Dunn, 1984; Jurado and Meza, 2017; Hamdaoui et al., 2018). Thus, it explains that gamers always simulate all the menus, features, elements and movements they face in the real world. Gamers actualise their gamification expertise based on cumulative concepts and theories (Manolis et al., 2013; Ladeira et al., 2016; Jurado and Meza, 2017). As a result, gamers always internalise technical and practical approaches to executing highly complex decision-making. On the other hand, this study argues that gamers confront the situation of narrowed periods and uninterrupted rests (Alexander, 2020; Olanipekun et al., 2020; Huang et al., 2021), resulting in dexterous memory and mental strength. Finally, the authors find no other choices for these gamers to choose learning styles of the convergent type.

This study finds that gamers acquire incremental knowledge with tacit-latent and kinetic-active learning. Furthermore, it explains that gamers should use these knowledge acquisitions to complete their loaded cognitions. This research also demonstrates that gamers comprehend their expertise through tacit-latent learning due to the need to engage in reflective practise (Howells, 1996; Erden et al., 2008; Wang et al., 2020). Furthermore, it demonstrates that gamers should permanently eliminate their curiosities, mental inferiorities and attitudinal anxieties. On the other hand, gamers could probably be engaged in kinetic-active knowledge acquisitions because they must update their high-skill capabilities (Strayer and Beitz, 2010; Jung J., 2020; Thongmak, 2020). Thus, the authors demonstrate that gamers always upgrade their capability to master gamification (Zebal et al., 2019; Chung and Jung, 2020; Thomas and Gupta, 2021) to win competitions. On the other hand, a gamer should arrange various procedures to practise them efficiently. Moreover, the gamer should direct procedurally decisive flows into a shortened mechanism due to the need for punctual decision-making (Linde, 2001; Arthurs, 2007; Liew et al., 2021). Finally, this study demonstrates that gamer behaviours improve their knowledge with conditionally elastic-active acquisitions. Hence, gamers maintain their kinetic-active ability to protect inferiority and maintain prestigious intellectuality.

The authors explicitly provide robust conclusive evidence that gamers' learning styles and knowledge acquisition end in measuring their cognitive combat readiness. We demonstrated that those approaches are superior to gamer behaviours with convergent types comprehended by tacit-latent and kinetic-active learning styles (Rosen and Martin, 1998; Tyler et al., 2012; Laanepere and Kasearu, 2021). Furthermore, this study infers that gamers shape their cognition to be innovative to challenge and attack their enemies in games (Hartman et al., 2006; Ladeira et al., 2016; Thongmak, 2020), such as army troopers. In addition, gamers' behavioural characteristics consistently improve their cognitive combat readiness because of future complex challenges. Moreover, gaining knowledge through tacit-latent and kinetic-active constructs of gamers' strong mentality (Silva et al., 2015;

TABLE 5 Hypothesis results.

| Hyp. | Mean (SD) | Cells | Mean (SD) | Cells | Mean diff. (*t*-value) |
|---|---|---|---|---|---|
| H1 | 4.537 (0.487) | Active-Convergent | 3.139 (0.8147) | Accommodative | 1.3978 (10.872)*** |
| | | | 4.054 (0.5715) | Divergent | 0.4831 (4.404)*** |
| | | | 3.460 (0.9660) | Assimilative | 1.0769 (7.278)*** |
| | | | 3.588 (0.8452) | All above | 0.7991 (7.449)*** |
| | 4.387 (0.563) | Latent-Convergent | 3.849 (1.0322) | Accommodative | 0.5379 (3.438)** |
| | | | 3.613 (0.9102) | Divergent | 0.7745 (5.304)*** |
| | | | 3.907 (0.6420) | Assimilative | 0.4807 (3.562)** |
| | | | 3.706 (0.9464) | All above | 0.6810 (5.763)*** |
| H2 | 4.111 (0.792) | Tacit | 3.744 (0.9780) | Material | 0.3672 (3.924)*** |
| H3 | 4.087 (0.690) | Kinetic | 3.628 (0.9635) | Actor | 0.4587 (7.356)*** |
| H4 | 4.477 (0.596) | Convergent-Tacit | 3.613 (0.9102) | Accommodative-Material | 0.8646 (4.702)*** |
| | | | 3.000 (1.2162) | Divergent-Material | 1.4775 (6.361)*** |
| | | | 3.817 (0.8457) | Assimilative-Material | 0.6608 (3.745)*** |
| | | | 3.506 (1.0333) | All above | 0.9717 (5.343)** |
| H5 | 4.586 (0.505) | Convergent-Kinetic | 3.139 (0.8147) | Accommodative-Actor | 1.4465 (8.949)*** |
| | | | 3.460 (0.9660) | Divergent-Actor | 1.1256 (5.994)*** |
| | | | 3.213 (0.8776) | Assimilative-Actor | 1.3731 (8.027)*** |
| | | | 3.258 (0.8823) | All above | 1.3276 (8.558)*** |
| Robustness: Field-experiment score | | | | | |
| H5 | 4.622 (0.285) | Convergent-Kinetic | 4.430 (0.2748) | Accommodative-Actor | 0.1915 (2.805)* |
| | | | 4.280 (0.4780) | Divergent-Actor | 0.3416 (3.525)** |
| | | | 4.389 (0.2914) | Assimilative-Actor | 0.2327 (3.290)** |
| | | | 4.372 (0.3521) | All above | 0.2495 (3.805)*** |

Király and Demetrovics, 2017; Rozgonjuk et al., 2021) uses the attitudinal and behavioural improvements as aggressors. This elastic-active knowledge acquisition also supports the gamers' cognitive combat readiness in building team loyalty (Hanson, 2003; Sumino and Harada, 2004; Mandryk and Birk, 2017). Moreover, the authors explain that gamers use cognitive combat readiness to win the pressured matches, execute punctual decisions (Tyler et al., 2012; Tsarouhas and Makrygianni, 2017; Laanepere and Kasearu, 2021) and compete in a chaotically pressured environment (McAllister et al., 2013; Alexander, 2020; Sumiyana et al., 2022). Finally, this study suggests that gamers have an alternative option to learn convergently and acquire knowledge with a tacit-latent and elastic-active style due to achieving superiority in cognitive combat readiness and reaching strong-mental combat readiness.

This study has implications for vocational learning systems and procedures concentrating on appropriate learning styles and knowledge acquisition. As with gamer behaviours, vocational students should train and educate themselves to achieve high cognitive work readiness (Strandenes et al., 2013; Zebal et al., 2019; Lei et al., 2021). This study demonstrates that achieving mental work readiness frames different learning systems and procedures: convergent learning styles and knowledge acquisitions with tacit-latent or kinetic-active styles. Furthermore, this study explains that vocational students get their capabilities and competencies according to an industry's needs. In other words, academic and vocational learning must arrange its learning system to create human resources ready to practise work (Barlett et al., 2009; Manolis et al., 2013; Hamdaoui et al., 2018) supported by student-centred learning systems. Thus, academic and vocational learning or training institutions treat students according to convergent learning styles. Likewise, this study argues for the need to treat vocational students with learning methods and a curriculum to lead them to focus on tacit-latent and kinetic-active learning. Finally, this study believes that curriculum designs in learning methods and knowledge mastery, like the behaviour of these gamers, have the lowest production cost in creating cognitive work readiness.

This study emphasises the supremacy of cognitive combat readiness as the final embodiment of learning styles and knowledge acquisition. Therefore, conceptually, it demonstrates the crucial uses of cognitive work readiness for academic and vocational learning and skills training systems. The superiority of this cognitive work readiness refers to the inference of mental combat readiness with the specification of beliefs, attitudes, and behaviours that concentrate on reactive and explorative abilities (Herspring, 2006; Strandenes et al., 2013; Tsarouhas and Makrygianni, 2017). Furthermore, this study demonstrates the power of young human resources with a signified engagement that, environmentally speaking, aligns with the conditionalism of student cognition in achieving competitive performances (Chen et al., 2016; Bustamante et al., 2020; Dantas and Cunha, 2020). Thus, the high-cognitive readiness of students would gain incremental capabilities and competencies (Tsarouhas and

Makrygianni, 2017; Sanjamsai and Phukao, 2018; Khanmurzina et al., 2020). On the other hand, they can work with a high level of team loyalty and a strong mentality in the face of complex challenges, pressured matches, and chaotic environments. The authors demonstrate that vocational students and trainees should be permanently within a state of cognitive work readiness when they enter the workforce to be genuinely competent.

## Conclusion, limitation, and future research

This study concludes that gamers exhibit convergent learning styles and acquire knowledge by tacit-latent and kinetic-active. Furthermore, it measures gamers' cognitive combat readiness, learning styles and knowledge acquisition consequences. Moreover, this study suggests that with high intellectuality markers, gamer behaviour focuses on learning style models and knowledge acquisition to improve capabilities and competencies, primarily cognitive combat readiness. Likewise, gamers are always consistent in their learning styles and knowledge acquisition, giving them adaptive power for problem-solving, high reasoning power, responsibility to act, etc. Furthermore, this study explains that academic and vocational learning and training systems must be designed to bring students high cognitive work readiness. Thus, they will have solid skills and expertise to enter the workforce with adequate capabilities and competencies.

### Limitations and future research

Having completed this research, the authors acknowledge weaknesses affecting the robustness of the validity of the conclusions. First, this study does not include the gamers' personalities, resulting in different learning styles and knowledge acquisition patterns. Then, it explains that gamers' characteristics, such as confront- and transform-proactive personalities, could affect other knowledge acquisitions resulting in high cognitive combat readiness. Finally, excluding gamers' personalities has consequences regarding the weakness of future research generalisation because character influences teammate loyalty, integrity, and patience. Second, this study's results deserve attention because they do not measure gamers' intelligence quotient. On the other hand, this study acknowledges that the intelligence quotient influences learning styles and knowledge acquisition. Likewise, the intelligence quotient constructs a different cognitive combat readiness, leading to more excellence. Therefore, future studies could complement this by establishing how the intelligence quotient determines gamers' learning styles and knowledge patterns.

Third, the authors recognise that this research method classifies gamers with a questionary design, impacting that we inferred the analysis results in affirmative biases. Meanwhile, we compared mean values of gamers' cognitive combat readiness as the consequenced measurements. Thus, it opens opportunities for future research to ascertain no affirmative biases using comparisons of gamers versus non-gamers, gamers versus other gamers, and non-gamers versus others. Finally, this study recommends setting gamers' self-control levels to make this future research more attractive. In essence, gamers' self-control indicates their maturity level in social life, which affects cognitive combat readiness. However, this research underlines that gamers' life-maturity levels result from their knowledge acquisition from past experiential values that will strongly dominate their attitudes and behaviours in the future.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

## Funding

University of Gadjah Mada – Research Directorate —2022 financed this research up to publication.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Publisher's note



## Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2022.1062922/full#supplementary-material

## References


Abel, A. D., Schneider, J., and Maguire, M. J. (2018). N400 response indexes word learning from linguistic context in children. *Lang. Learn. Dev.* 14, 61–71. doi: 10.1080/15475441.2017.1362347

Al Shaikh, A., Aldarmahi, A. A., Ebtehal, A.-S., Subahi, A., Ahmed, M. E., Hydrie, M. Z., et al. (2019). Learning styles and satisfaction with educational activities of Saudi health science university students. *J. Taibah Univ. Med. Sci.* 14, 418–424. doi: 10.1016/j.jtumed.2019.07.002

Alberti, F. G., and Pizzurno, E. (2015). Knowledge exchanges in innovation networks: evidences from an Italian aerospace cluster. *Compet. Rev.* 25, 258–287. doi: 10.1108/CR-01-2015-0004

Alexander, E. (2020). Purposeful simulation role assignment. *Clin. Simul. Nurs.* 48, 1–7. doi: 10.1016/j.ecns.2020.07.008

Allinson, C. W., and Hayes, J. (1996). The cognitive style index: a measure of intuition-analysis for organisational research. *J. Manag. Stud.* 33, 119–135. doi: 10.1111/j.1467-6486.1996.tb00801.x

Andreou, C., Papastavrou, E., and Merkouris, A. (2014). Learning styles and critical thinking relationship in baccalaureate nursing education: a systematic review. *Nurse Educ. Today* 34, 362–371. doi: 10.1016/j.nedt.2013.06.004

Arthurs, J. B. (2007). A juggling act in the classroom: managing different learning styles. *Teach. Learn. Nurs.* 2, 2–7. doi: 10.1016/j.teln.2006.10.002

Banner, G., and Rayner, S. (2000). Learning language and learning style: principles, process and practice. *Lang. Learn. J.* 21, 37–44. doi: 10.1080/09571730085200091

Barlett, C. P., Anderson, C. A., and Swing, E. L. (2009). Video game effects—confirmed, suspected, and speculative: a review of the evidence. *Simul. Gaming* 40, 377–403. doi: 10.1177/1046878108327539

Breen, R., and Lindsay, R. (1999). Academic research and student motivation. *Stud. High. Educ.* 24, 75–93. doi: 10.1080/03075079912331380158

Bustamante, A. S., Schlesinger, M., Begolli, K. N., Golinkoff, R. M., Shahidi, N., Zonji, S., et al. (2020). More than just a game: transforming social interaction and STEM play with Parkopolis. *Dev. Psychol.* 56, 1041–1056. doi: 10.1037/dev0000923

Cegarra-Navarro, J.-G., Jiménez-Jiménez, D., and García-Pérez, A. (2019). An integrative view of knowledge processes and a learning culture for ambidexterity: toward improved organisational performance in the banking sector. *IEEE Trans. Eng. Manag.* 68, 408–417. doi: 10.1109/TEM.2019.2917430

Chen, A., Lu, Y., and Wang, B. (2016). Enhancing perceived enjoyment in social games through social and gaming factors. *Inf. Technol. People* 29, 99–119. doi: 10.1108/ITP-07-2014-0156

Chung, K., and Jung, H. (2020). Knowledge-based dynamic cluster model for healthcare management using a convolutional neural network. *Inf. Technol. Manag.* 21, 41–50. doi: 10.1007/s10799-019-00304-1

Dale, G., and Green, C. S. (2017). The changing face of video games and video gamers: future directions in the scientific study of video game play and cognitive performance. *J. Cognit. Enhancement* 1, 280–294. doi: 10.1007/s41465-017-0015-6

Dantas, L. A., and Cunha, A. (2020). An integrative debate on learning styles and the learning process. *Social Sci. Humanities Open* 2:100017. doi: 10.1016/j.ssaho.2020.100017

Dodd, T. H., Laverie, D. A., Wilcox, J. F., and Duhan, D. F. (2005). Differential effects of experience, subjective knowledge, and objective knowledge on sources of information used in consumer wine purchasing. *J. Hospitality Tourism Res.* 29, 3–19. doi: 10.1177/1096348004267518

Drachen, A., Sifa, R., and Thurau, C. (2014). The name in the game: patterns in character names and gamer tags. *Entertainment Comput.* 5, 21–32. doi: 10.1016/j.entcom.2014.02.001

Dufwenberg, M., Sundaram, R., and Butler, D. J. (2010). Epiphany in the game of 21. *J. Econ. Behav. Organ.* 75, 132–143. doi: 10.1016/j.jebo.2010.03.025

Erden, Z., Von Krogh, G., and Nonaka, I. (2008). The quality of group tacit knowledge. *J. Strateg. Inf. Syst.* 17, 4–18. doi: 10.1016/j.jsis.2008.02.002

Ewell, P. J., Hamilton, J. C., and Guadagno, R. E. (2018). How do video game players identify their actions? Integrating action identification theory and videogame play via the behavior identification form-gamer. *Comput. Hum. Behav.* 81, 189–197. doi: 10.1016/j.chb.2017.12.019

Fox, J., Gilbert, M., and Tang, W. Y. (2018). Player experiences in a massively multiplayer online game: a diary study of performance, motivation, and social interaction. *New Media Soc.* 20, 4056–4073. doi: 10.1177/1461444818767102

García-Campos, M.-D., Canabal, C., and Alba-Pastor, C. (2020). Executive functions in universal design for learning: moving towards inclusive education. *Int. J. Incl. Educ.* 24, 660–674. doi: 10.1080/13603116.2018.1474955

Garcia-Manero, G., Fenaux, P., Al-Kali, A., Baer, M. R., Sekeres, M. A., Roboz, G. J., et al. (2016). Rigosertib versus best supportive care for patients with high-risk myelodysplastic syndromes after failure of hypomethylating drugs (ONTIME): a randomised, controlled, phase 3 trial. *Lancet Oncol.* 17, 496–508. doi: 10.1016/S1470-2045(16)00009-7

Garner, I. (2000). Problems and inconsistencies with Kolb's learning styles. *Educ. Psychol.* 20, 341–348. doi: 10.1080/713663745

Giampaoli, D., Ciambotti, M., and Bontis, N. (2017). Knowledge management, problem solving and performance in top Italian firms. *J. Knowl. Manag.* 21, 355–375. doi: 10.1108/JKM-03-2016-0113

Gneezy, U., Rustichini, A., and Vostroknutov, A. (2010). Experience and insight in the race game. *J. Econ. Behav. Organ.* 75, 144–155. doi: 10.1016/j.jebo.2010.04.005

Goulding, J., and Syed-Khuzzan, S. (2014). A study on the validity of a four-variant diagnostic learning styles questionnaire. *Education + Training* 56, 141–164. doi: 10.1108/ET-11-2012-0109

Gray, P. H. (2001). A problem-solving perspective on knowledge management practices. *Decis. Support. Syst.* 31, 87–102. doi: 10.1016/S0167-9236(00)00121-4

Griffith, J. (2002). Multilevel analysis of cohesion's relation to stress, well-being, identification, disintegration, and perceived combat readiness. *Mil. Psychol.* 14, 217–239. doi: 10.1207/S15327876MP1403_3

Griffith, J. (2006). What do the soldiers say? Needed ingredients for determining unit readiness. *Armed Forces Soc.* 32, 367–388. doi: 10.1177/0095327X05280555

Griggs, S. A., and Dunn, R. S. (1984). Selected case studies of the learning style preferences of gifted students. *Gifted Child Q.* 28, 115–119. doi: 10.1177/001698628402800304

Hamdaoui, N., Khalidi Idrissi, M., and Bennani, S. (2018). Modelling learners in educational games: relationship between playing and learning styles. *Simul. Gaming* 49, 675–699. doi: 10.1177/1046878118783804

Hanson, T. E. (2003). The eighth Army's combat readiness before Korea: a new appraisal. *Armed Forces Soc.* 29, 167–184. doi: 10.1177/0095327X0302900202

Hartman, J. B., Shim, S., Barber, B., and O'Brien, M. (2006). Adolescents' utilitarian and hedonic web consumption behavior: hierarchical influence of personal values and innovativeness. *Psychol. Mark.* 23, 813–839. doi: 10.1002/mar.20135

Herspring, D. R. (2006). Undermining combat readiness in the Russian military, 1992-2005. *Armed Forces Soc.* 32, 513–531. doi: 10.1177/0095327X06288030

Hilvert-Bruce, Z., and Neill, J. T. (2020). I'm just trolling: the role of normative beliefs in aggressive behaviour in online gaming. *Comput. Hum. Behav.* 102, 303–311. doi: 10.1016/j.chb.2019.09.003

Hong, X., Zhang, B., Liu, Y., Qi, H., and Li, W. (2021). Deep-learning-based guided wave detection for the liquid-level state in porcelain bushing type terminal. *Struct. Control. Health Monit.* 28:e2651. doi: 10.1002/stc.2651

Howells, J. (1996). Tacit knowledge. *Tech. Anal. Strat. Manag.* 8, 91–106. doi: 10.1080/09537329608524237

Huang, T.-L., Teng, C.-I., Tai, S.-I., Chen, H., and Dennis, A. R. (2021). Power structure builds gamer loyalty. *Decis. Support. Syst.* 154:113696. doi: 10.1016/j.dss.2021.113696

Hung, S. Y., Lai, H. M., and Chou, Y. C. (2015). Knowledge-sharing intention in professional virtual communities: a comparison between posters and lurkers. *J. Assoc. Inf. Sci. Technol.* 66, 2494–2510. doi: 10.1002/asi.23339

Hung, C.-H., and Lin, C.-Y. (2015). Using concept mapping to evaluate knowledge structure in problem-based learning. *BMC Med. Educ.* 15, 212–219. doi: 10.1186/s12909-015-0496-x

Jayalath, J., and Esichaikul, V. (2020). Gamification to enhance motivation and engagement in blended eLearning for technical and vocational education and training. *Technol. Knowl. Learn.* 27, 91–118. doi: 10.1007/s10758-020-09466-2

Johannessen, J.-A. (2021). "Leadership tools to increase the motivation of knowledge workers," in *Continuous Change and Communication in Knowledge Management* (Bingley, UK: Emerald Publishing Limited), 75–102.

Johnson, B. (2010). A few good boys: masculinity at a military-style charter school. *Men Masculinities* 12, 575–596. doi: 10.1177/1097184X09342228

Jung, C. W. (2020). Role of gamers' communicative ecology on game community involvement and self-identification of gamer. *Comput. Hum. Behav.* 104:106164. doi: 10.1016/j.chb.2019.106164

Jung, J. (2020). The fourth industrial revolution, knowledge production and higher education in South Korea. *J. High. Educ. Policy Manag.* 42, 134–156. doi: 10.1080/1360080X.2019.1660047

Jurado, F., and Meza, R. E. (2017). An exploratory study in the use of gamer profiles and learning styles to build educational video games. *Int. J. Eng. Educ.* 33, 797–806.

Kamal, A., and Radhakrishnan, S. (2019). Individual learning preferences based on personality traits in an E-learning scenario. *Educ. Inf. Technol.* 24, 407–435. doi: 10.1007/s10639-018-9777-4

Keefe, J. W. (1979). "Learning style: an overview," in *Student Learning Styles: Diagnosing and Prescribing Programs*. National Association of Secondary School Principals, Reston, Virginia, United Stated *Vol. 1*. 1–17.

Khanmurzina, R. R., Cherdymova, E. I., Guryanova, T. Y., Toriia, R. A., Sukhodolova, E. M., and Tararina, L. I. (2020). Computer games influence on everyday social practices of students-gamers. *Contemp. Educ. Technol.* 11, 11–19. doi: 10.30935/cet.641753

Khenissi, M. A., Essalmi, F., Jemni, M., Graf, S., and Chen, N.-S. (2016). Relationship between learning styles and genres of games. *Comput. Educ.* 101, 1–14. doi: 10.1016/j.compedu.2016.05.005

Király, O., and Demetrovics, Z. (2017). Inclusion of gaming disorder in ICD has more advantages than disadvantages: commentary on: scholars' open debate paper on the World Health Organization ICD-11 gaming disorder proposal (Aarseth et al.). *J. Behav. Addict.* 6, 280–284. doi: 10.1556/2006.6.2017.046

Kolb, A. Y., and Kolb, D. A. (2005). Learning styles and learning spaces: enhancing experiential learning in higher education. *Acad. Manag. Learn. Edu.* 4, 193–212. doi: 10.5465/amle.2005.17268566

Laanepere, T., and Kasearu, K. (2021). Military and civilian field–related factors in Estonian reservists' military service readiness. *Armed Forces Soc.* 47, 690–709. doi: 10.1177/0095327X20944093

Ladeira, W. J., de Santini, F. O., Sampaio, C. H., and Araujo, C. F. (2016). Experiential value and domain-specific innovativeness during freemium game usage: effects on child well-being. *Young Consum.* 17, 64–77. doi: 10.1108/YC-07-2015-00538

Lei, H., Gui, L., and Le, P. B. (2021). Linking transformational leadership and frugal innovation: the mediating role of tacit and explicit knowledge sharing. *J. Knowl. Manag.* 25, 1832–1852. doi: 10.1108/JKM-04-2020-0247

Li, H., and Wang, S. (2013). The role of cognitive distortion in online game addiction among Chinese adolescents. *Child Youth Serv. Rev.* 35, 1468–1475. doi: 10.1016/j.childyouth.2013.05.021

Liew, C. L., Yeates, J., and Lilley, S. C. (2021). Digitised indigenous knowledge collections: impact on cultural knowledge transmission, social connections, and cultural identity. *J. Assoc. Inf. Sci. Technol.* 72, 1575–1592. doi: 10.1002/asi.24536

Linde, C. (2001). Narrative and social tacit knowledge. *J. Knowl. Manag.* 5, 160–171. doi: 10.1108/13673270110393202

Mandryk, R. L., and Birk, M. V. (2017). Toward game-based digital mental health interventions: player habits and preferences. *J. Med. Internet Res.* 19:e128. doi: 10.2196/jmir.6906

Manolis, C., Burns, D. J., Assudani, R., and Chinta, R. (2013). Assessing experiential learning styles: a methodological reconstruction and validation of the Kolb learning style inventory. *Learn. Individ. Differ.* 23, 44–52. doi: 10.1016/j.lindif.2012.10.009

McAllister, G., Mirza-Babaei, P., and Avent, J. (2013). "Improving gameplay with game metrics and player metrics," in *Game Analytics*. eds. M. S. El-Nasr, A. Drachen, A. Canos (London, UK: Springer), 621–638.

McCrow, J., Sullivan, K. A., and Beattie, E. R. (2014). Delirium knowledge and recognition: a randomised controlled trial of a web-based educational intervention for acute care nurses. *Nurse Educ. Today* 34, 912–917. doi: 10.1016/j.nedt.2013.12.006

Müller-Wienbergen, F., Müller, O., Seidel, S., and Becker, J. (2011). Leaving the beaten tracks in creative work–a design theory for systems that support convergent and divergent thinking. *J. Assoc. Inf. Syst.* 12, 714–740. doi: 10.17705/1jais.00280

Nacke, L. E., Bateman, C., and Mandryk, R. L. (2014). BrainHex: a neurobiological gamer typology survey. *Entertainment Comput.* 5, 55–62. doi: 10.1016/j.entcom.2013.06.002

Olanipekun, T., Effoe, V., Bakinde, N., Bradley, C., Ivonye, C., and Harris, R. (2020). Learning styles of internal medicine residents and association with the in-training examination performance. *J. Natl. Med. Assoc.* 112, 44–51. doi: 10.1016/j.jnma.2019.12.002

Papa, E., Coppola, P., Angiello, G., and Carpentieri, G. (2017). The learning process of accessibility instrument developers: testing the tools in planning practice. *Transp. Res. A Policy Pract.* 104, 108–120. doi: 10.1016/j.tra.2017.03.010

Park, C. W., and Moon, B. J. (2003). The relationship between product involvement and product knowledge: moderating roles of product type and product knowledge type. *Psychol. Mark.* 20, 977–997. doi: 10.1002/mar.10105

Peter, S. C., Brett, E. I., Suda, M. T., Leavens, E. L., Miller, M. B., Leffingwell, T. R., et al. (2019). A meta-analysis of brief personalised feedback interventions for problematic gambling. *J. Gambl. Stud.* 35, 447–464. doi: 10.1007/s10899-018-09818-9

Rosen, L. N., and Martin, L. (1998). Sexual harassment, cohesion, and combat readiness in US Army support units. *Armed Forces Soc.* 24, 221–244. doi: 10.1177/0095327X9702400202

Rozgonjuk, D., Schivinski, B., Pontes, H. M., and Montag, C. (2021). Problematic online behaviors among gamers: the links between problematic gaming, gambling, shopping, pornography use, and social networking. *Int. J. Ment. Heal. Addict.* 1-18, 1–18. doi: 10.1007/s11469-021-00590-3

Sadler-Smith, E., and Riding, R. (1999). Cognitive style and instructional preferences. *Instr. Sci.* 27, 355–371. doi: 10.1023/A:1003277503330

Sahasrabudhe, V., and Kanungo, S. (2014). Appropriate media choice for e-learning effectiveness: role of learning domain and learning style. *Comput. Educ.* 76, 237–249. doi: 10.1016/j.compedu.2014.04.006

Sánchez, J., and Olivares, R. (2011). Problem solving and collaboration using mobile serious games. *Comput. Educ.* 57, 1943–1952. doi: 10.1016/j.compedu.2011.04.012

Sanjamsai, S., and Phukao, D. (2018). Flow experience in computer game playing among Thai university students. *Kasetsart J. Social Sci.* 39, 175–182. doi: 10.1016/j.kjss.2018.03.003

Seo, K., Fels, S., Kang, M., Jung, C., and Ryu, H. (2021). Goldilocks conditions for workplace gamification: how narrative persuasion helps manufacturing workers create self-directed behaviors. *Hum–Comput. Interact.* 36, 473–510. doi: 10.1080/07370024.2020.1744145

Silva, G. F. M., Raposo, A., and Suplino, M. (2015). Exploring collaboration patterns in a multitouch game to encourage social interaction and collaboration among users with autism spectrum disorder. *Comput. Supported Cooperative Work (CSCW)* 24, 149–175. doi: 10.1007/s10606-014-9214-1

Strandenes, G., Skogrand, H., Spinella, P. C., Hervig, T., and Rein, E. B. (2013). Donor performance of combat readiness skills of special forces soldiers are maintained immediately after whole blood donation: a study to support the development of a prehospital fresh whole blood transfusion program. *Transfusion* 53, 526–530. doi: 10.1111/j.1537-2995.2012.03767.x

Strayer, R. M., and Beitz, J. M. (2010). Factors influencing pharmacology knowledge acquisition in traditional versus nontraditional baccalaureate nursing students. *J. Prof. Nurs.* 26, 301–308. doi: 10.1016/j.profnurs.2010.02.001

Sumino, M., and Harada, M. (2004). Affective experience of J. league fans: the relationship between affective experience, team loyalty and intention to attend. *Manag. Leis.* 9, 181–192. doi: 10.1080/1360671042000273855

Sumiyana, S., Hadi, C., and Saputra, M. A. (2022). A new contemporary profession as game boosters: the Behavioural emergence of intellectual opportunism. *Hum. Behav. Emerg. Technol.* 2022, 1–14. doi: 10.1155/2022/8046012

Teng, C.-I. (2008). Personality differences between online game players and nonplayers in a student sample. *Cyberpsychol. Behav.* 11, 232–234. doi: 10.1089/cpb.2007.0064

Thomas, A., and Gupta, V. (2021). Tacit knowledge in organisations: bibliometrics and a framework-based systematic review of antecedents, outcomes, theories, methods and future directions. *J. Knowl. Manag.* 26, 1014–1041. doi: 10.1108/JKM-01-2021-0026

Thongmak, M. (2020). Determinants of intention to play Pokémon go. *Heliyon* 6:e03895. doi: 10.1016/j.heliyon.2020.e03895

Toth, I., Heinänen, S., and Nisula, A.-M. (2020). Personal resources and knowledge workers' job engagement. *Int. J. Organ. Anal.* 28, 595–610. doi: 10.1108/IJOA-07-2019-1830

Tsarouhas, P., and Makrygianni, M. (2017). A framework for maintenance and combat readiness management of a jet fighter aircraft. *Int. J. Syst. Assur. Eng. Manage.* 8, 1895–1909. doi: 10.1007/s13198-016-0481-8

Tyler, J. A., Ritchie, J. D., Leas, M. L., Edwards, K. D., Eastridge, B. E., White, C. E., et al. (2012). Combat readiness for the modern military surgeon: data from a decade of combat operations. *J. Trauma Acute Care Surg.* 73, S64–S70. doi: 10.1097/TA.0b013e3182625ebb

Van der Lingen, E., Åmo, B. W., and Pettersen, I. B. (2020). The relationship between entrepreneurial experience and preferred learning styles. *Education + Training* 62, 863–876. doi: 10.1108/ET-11-2019-0263

Visser-Wijnveen, G. J., van der Rijst, R. M., and van Driel, J. H. (2016). A questionnaire to capture students' perceptions of research integration in their courses. *High. Educ.* 71, 473–488. doi: 10.1007/s10734-015-9918-2

Wang, L., Song, M., Zhang, M., and Wang, L. (2020). How does contract completeness affect tacit knowledge acquisition? *J. Knowl. Manag.* 25, 989–1005. doi: 10.1108/JKM-02-2020-0130

Willingham, D. T., Hughes, E. M., and Dobolyi, D. G. (2015). The scientific status of learning styles theories. *Teach. Psychol.* 42, 266–271. doi: 10.1177/0098628315589505

Yousef, D. A. (2016). The use of the learning styles questionnaire (LSQ) in the United Arab Emirates. *Qual. Assur. Educ.* 24, 490–506. doi: 10.1108/QAE-03-2016-0010

Yurechko, J. J. (1988). The soviet combat readiness system. *J. Soviet Mil. Stud.* 1, 231–242. doi: 10.1080/13518048808429909

Zebal, M., Ferdous, A., and Chambers, C. (2019). An integrated model of marketing knowledge–a tacit knowledge perspective. *J. Res. Mark. Entrep.* 21, 2–18. doi: 10.1108/JRME-03-2018-0018

Zimmermann, M., Schopf, D., Lütteken, N., Liu, Z., Storost, K., Baumann, M., et al. (2018). Carrot and stick: a game-theoretic approach to motivate cooperative driving through social interaction. *Transp. Res. Part C: Emerg. Technol.* 88, 159–175. doi: 10.1016/j.trc.2018.01.017