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Scaling up computational thinking skills in computer-assisted language learning (CTsCALL) and its fitness with language learners' intentions to use virtual exchange: A bi-symmetric approach

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ABSTRACT

Many studies have demonstrated that Virtual Exchange (VE) for teaching languages can have a positive effect on learners' intercultural awareness or achievements. However, during this century, the teaching process has shifted from teaching with technology to solving problems with it. In this regard, pedagogical experts in Science, Technology, Engineering, and Mathematics (STEM) have developed programming and robotics based on Computational Thinking skills (CTs), which have been regarded as the core of 21st-century skills. In the field of CALL, this skill has received very little attention. Accordingly, we have attempted to switch the process and outcome of language learning in VE. Thus, we developed the conceptual framework that integrated CTsCALL and Individual-technology-task-environment Fit (ITTEF). Having designed our VE tasks based on CTsCALL, we provided the opportunity for 92 Spanish language learners in our project to exchange language and culture with Cypriot and Irish students and solve VE tasks based on CTsCALL. The result of the symmetric phase of the study validated the five-dimensional structure of CTsCALL and the four-dimensional structures of ITTEF in VE and CALL. It also revealed that language learners, who focused on the key information rather than the details while solving language tasks, as well as recognizing the pattern of task solving and applying them to other tasks, found VE, and CTsCALL to be aligned with their current capabilities, learning environment, and problem-solving skills that mediated their intention to learn and exchange information in this context in the future. Furthermore, the asymmetrical part of the study revealed that sixteen solutions are available to shape language learners' continued intention to use VE by combining the components of CTsCALL and ITTEF. Thus, the study developed the CTsCALL questionnaire and its theory into CALL together with the Council of Europe's Common European Framework of Reference for Languages and recommended that CALL researchers and educators take a broader view of VE, as well as continuing to validate CTsCALL in other CALL disciplines to show that this skill belongs to CALL as well.

1. Introduction

Several educational organizations call for the development and integration of information and communication technologies to enhance skill sets, particularly in education, fostering what is known as '21st-century digital skills' introduced by organizational experts such as Assessment and Teaching of Twenty-First Century Skills, the Organization for Economic Co-operation and Development, the European Union, the Computer Science Teachers Association, the International Society for Technology in Education, and the International Association for the Evaluation of Educational Achievement. The primary goal of these initiatives is to underscore the importance of technology-based pedagogy in addressing 21st-century challenges. This pedagogy equips learners and teachers with 21st-century skills such as algorithmic thinking, problem-solving, and creativity, enabling them to meet the challenges of the 21st -century (Rahimi, 2024b).

The foundation of these skills lies CT, which enables students to enhance their creativity and problem-solving abilities, helping them address increasingly complex challenges efficiently using ICT (Cheng et al., 2023). In this regard, both the CSTA and ISTE recommend that all learners acquire CT skills to foster greater creativity and digital problem-solving capabilities, integrating AI and ICT in both their academic and everyday lives (Tang et al., 2020). Consequently, educators

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Abbreviations

Computational thinking (CT)
Computer-Assisted Language Learning (CALL)
Computational Thinking skills in Computer Assisted Language Learning (CTsCALL)
Virtual exchange (VE)
Task Technology Fit (TTF)
English as a Foreign Language (EFL)
Task-technology-fit (TTF)
Individual-technology fit (ITF)
Environmental-technology fit (ETF)
Intention to use (ITU)
Intercultural communicative competence (ICC)
Technology acceptance models (TAM)
The Unified Theory of Acceptance and Use of Technology (UTAUT)
Theory of Planned Behavior (TPB)
Language Massive Open Online Course (LMOOC)
Mobile-Assisted Language Learning (MALL)
Algorithmic thinking (AL)
Abstraction (AB)
Collaboration (CL)
Evaluation (EV)
Generalization (GE)
Kaiser-Meyer-Olkin (KMO)
Confirmatory Factor Analysis (CFA)
Exploratory Factor Analysis (EFA)
Composite Reliability (CR)
Average variance and maximum squared variance (MSV)
Analysis of Moment Structure (AMOS)
Heterotrait-Monotrait ratio (HTMT)
Comparative Fit Index (CFI)
Root Mean Square Error of Approximation (RMSEA)
Null Hypothesis Significance Test (NHST)
Analyze of variances (ANOVA)
Fuzzy-Set Qualitative Comparative Analysis (fsQCA)
Crisp-Set Qualitative Comparative Analysis (csQCA)
Average Variance Extracted (AVE)
Variance Inflation Factor (VIF)
Confidence Intervals (CI)
Goodness of Fit Index (GOF)
Standardized Root Mean Square Residual (SRMR)

should equip students with these skills to prepare them for their future endeavors (Rahimi, 2024a,b; Rahimi & Mosalli, 2024; Tang et al., 2020). Through the use of computer programming, robotics, and other ICT tools, STEM disciplines provide comprehensive exposure to CT, with some even considering it a specialized skill within STEM education (Chevalier, Giang, Piatti, & Mondada, 2020; Israel-Fishelson & Hershkovitz, 2022). However, CT should not be viewed as a skill exclusive to STEM education, robotics, or data coding; instead, it should be recognized as "the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that an information-processing agent can effectively carry out" (Wing, 2006; as cited in Tang et al., 2020, p. 1).

Recent research across various fields has integrated CT into their studies (e.g., Chevalier, Giang, Piatti, & Mondada, 2020; Kong & Lai, 2023). However, the CALL community has yet to address this gap. As technology evolves, the field of CALL will undoubtedly continue to progress (Colpaert, 2020; Gimeno-Sanz, 2015), and as CALL researchers, we should actively contribute to its expansion. Moreover, recent CALL scholars have advocated for the integration of 21st-century digital skills alongside language teaching competencies in CALL (Rahimi, 2024b; Rahimi & Mosalli, 2024). To address this gap by following CALL pioneers' recommendations, we attempt to validate and develop this new conceptual framework for the CALL, accordingly the first phase of the present study will attempt to develop and validate a new conceptual framework of CT specifically for the CALL field, particularly in the VE environment.

ICT has also enhanced CALL, giving rise to a new subfield, VE, which focuses on online intercultural communication and collaboration to develop linguistic, social, intercultural and digital competences (Colpaert, 2020). Over the past decade, VE has flourished, promoting second-language skills (Luo & Gui, 2019), subskills (Liu, Yao, Tao, & Yang, 2023a, 2023b), digital competence (Sevilla-Pavón & Nicolaou, 2020), motivational factors (Rahimi & Sevilla-Pavón, 2025), and intercultural communicative competence (ICC). However, recently scholars, particularly Colpaert (2020) and O'Dowd (2021), have pointed out that CALL research has concentrated more on outcomes than on understanding the underlying mechanisms of how VE functions. In their systematic and integrative review of VE, O'Dowd (2021) and Luo and Yang (2021) highlighted several key developments, especially its role in shaping learners' ICC, and called for further research to incorporate emerging trends. Given the multimodality, adaptability, directionality and collaboration inherent in VE, along with the identified recommendations and gaps, we have advanced the field by exploring its practical applications in fostering 21st-century digital skills, specifically through CTsCALL. This problem-solving-oriented framework may offer new insights for VE research, particularly in its potential role as a predictor variable, an area that has not yet been explored by VE and CALL researchers.

A recent CALL study has reported the positive effects of VE on language learning; however, there are few studies which have looked at its use from the point of view of users' intentions to use it. As a matter of fact, the success of any ICT, and CALL material depends on users' intention to use, particularly in terms of technology acceptance models (TAMs; Rahimi, 2023). A variety of TAM models have recently been integrated and validated by scholars within various CALL disciplines, including the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Planned Behavior (TPB), all of which have been validated by researchers in Language Massive Open Online Course LMOOCs (Rahimi, 2023) as well as Mobile Assisted Language Learning (MALL; Hsu & Lin, 2021). In terms of technology acceptance models, the VE field has been neglected by CALL researchers. This issue holds significant importance in VE, as it has the potential to bridge cultural gaps by determining participants' willingness to engage meaningfully with individuals from diverse cultures, social backgrounds, and educational experiences. This will expand the educational landscape, promote global collaboration, overcome technological and social barriers, as well as ensure the effective use of VE and computational thinking skills in this context. Furthermore, a recent systematic and hermeneutic literature review indicates that TAM, UTAUT, and TPB are commonly used to examine users' attitudes toward technology adoption (Granić, 2022; Sackstein et al., 2022). As a result of these gaps, this study focuses on the task-technology fit model (TTF; Goodhue & Thompson, 1995) in VE in order to enhance its predictive quality in predicting language users' ITU toward VE.

We position our research within the growing body of work that validates the factorial structure and scale of CT skills, ensuring that we remain aligned with other fields advancing 21st-century digital skills. By exploring the serial correlation between language learners' attitudes toward VE and their activities, we make a significant contribution to psycholinguistics, TAM and CALL research. Specifically, we apply a TTF framework to VE and propose a new conceptual model for this context. Furthermore, by employing a bisymmetric research design that

integrates both necessary and sufficiency logic (Rahimi & Sevilla-Pavón, 2024a), we aim to enhance the methodological approaches in CALL and VE literature. This is particularly relevant given recent calls for more quantitative research designs, as VE studies in the CALL field have predominantly relied on qualitative case studies (Rahimi & Sevilla-Pavón, 2025; Rienties et al., 2020). Accordingly, the study applied the bi-symmetrical approach, where the symmetrical part attempts to validate the factorial structure of the CT in VE and determine whether the study scale is valid, and applicable in humanistic fields, particularly in CALL, and VE, and explores the direct, indirect, and serial correlations between learners' CTsCALL skills and their intention to learn language in VE in the future. Alternatively, the asymmetrical analysis of the study will uncover the conditions that CTsCALL and Individual Technology Task Environment Fit (ITTEF) could integrate to shape language learners' intentions toward VE through fsQCA and configuration analysis. Hence the researchers propose the following research questions:

- RQ1: What are the factorial validity of the computational thinking skills in CALL (CTsCALL) in virtual exchange?
- RQ2: What components of computational thinking skills in CALL (CTsCALL) can predict learners' task-technology-fit, individual-technology-fit, and environmental-technology-fit?
- RQ3: To what extent the individual-technology-fit, task-technology-fit, and environmental-technology-fit can mediate the correlation between learners' CTsCALL and their intention to use VE in the future?
- RQ4: How many peripheral, and core conditions would be made available to shape the language learners' intention to use virtual exchange by the presence of computational thinking skills in CALL (CTsCALL) and Individual-technology-task-environment Fit (ITTEF)?

The first research question of this study focuses on validating the factorial structure of the CTsCALL scale, ensuring its relevance to the context. The second question explores the correlation between language learners' CTsCALL skills and their fitness with VE and individual skills. The third question investigates how this fitness mediates or moderates the relationship between learners' CTsCALL skills and their intention to use VE, following fuzzy logic.

By applying fsQCA, the study further illuminates the combination of CTsCALL and ITTEF, highlighting the core and peripheral conditions required to shape learners' behavioral intentions toward VE. Specifically, the second and third research questions examine the direct and indirect correlations between learners' CTsCALL and ITTEF skills and their behavioral intentions toward VE, based on shared values and fuzzy logic. The fourth research question offers a different perspective by merging all variables on a case-by-case basis, grounded in necessary logic.

2. Theoretical frameworks, and literature review

2.1. Computational thinking skills in CALL (CTsCALL)

Seymour Papert (1980) introduced CT to education, suggesting that computers could enhance thinking and change access patterns to knowledge. Further, he stressed the importance of providing all children with access to computers to facilitate learning and creativity (Papert, 1993). Wing (2006) then proposed integrating CT into K–12 curricula and researching efficient teaching methods to cultivate it. Since then, scholars have acknowledged it as the core of 21st-century skills, essential for students to study and live more effectively in the 21st century (Tang et al., 2020). Despite its common use in STEM education, its exact definition remains controversial. Thus, ISTE (2015) described CT as an asset to thinking skills, with the subcomponents of cooperation and collaboration, problem solving, critical thinking, creativity, and algorithmic thinking. The operationalization and conceptualization of CT vary depending on the ISTE definition and the researcher's field of study. Accordingly, in the current study, we define it as a higher-order thinking skill that allows language learners to solve language learning tasks through CALL materials, individually or collaboratively, and is transferable to another task and target language context. Thus, we operationalized CTs in CALL, and VE as follows:

- **Algorithmic thinking (AL):** language learners' skills in solving VE tasks step-by-step.
- **Abstraction (AB):** language learners' skills to focus on the key information rather than the details to solve a task in VE (deductive reasoning).
- **Collaboration (CL):** language learners' skills in cooperatively solving VE tasks.
- **Evaluation (EV):** language learners' skills in comparing different solutions and responses and selecting the most appropriate one.
- **Generalization (GE):** language learners' skills' to recognize the patterns of how to solve specific VE tasks and apply them to other language tasks or transfer them to target language contexts.

2.2. Task-technology fit framework

The interplay between a task and technology develops the concept of fit. Because of fit, it is important to align technology characteristics with the task, learners, and study environment. Recent studies highlight that the VE ecosystem presents both unique advantages and constraints that can influence learners' psychological factors, particularly their attitudes toward VE. Internet-mediated intercultural exchange is not only a highly complex social activity but also pedagogically challenging, as the environment, learners' goals, characteristics, skills and activities contribute to greater unpredictability and instability in learners' psychological behaviors (Liang et al., 2023; Rahimi & Sevilla-Pavón, 2025). This unpredictability may be further amplified by the integration of new skills, such as CTsCALL, alongside language skills, making it essential to explore how learners' individual skills, the VE environment and its tasks are interrelated in shaping their attitudes toward it—one of the key psychological factors. In this context, the tridimensional nature of the TTF framework offers advantages over other technology acceptance models like TAM, TPB and UTAUT. While these models focus on factors such as social norms, effort expectations, perceived behavioral control, ease of use and the usefulness of technology (Sackstein et al., 2022; Wang et al., 2021), they are not directly aligned with the objectives of this study.

Furthermore, the lack of fit between task and technology is called task-technology misfit (Howard & Rose, 2019). Misfit between task and technology occurs when the technology provides too few or too many features in order to complete the task. In other words, technology fits when it contains just the right number of features in comparison to a given task's requirements. It is the same with respect to individuals' capabilities as well as environmental characteristics (Liu et al., 2023; Lu and Yang, 2014), since the task should be aligned with a learner's capabilities in addition to the study environment. Thus, the tri-dimensional nature of TTF framework made it suitable for achieving our study's goal, which is to determine to what extent CT can be fit to VE and students' abilities. Considering the study context, the authors defined the following components:

- **Task-technology-fit (TTF):** the degree to which language tasks derived from CTsCALL are in accordance with VE features and context.
- **Individual-technology fit (ITF):** the extent to which language learners' abilities and skills match the VE environment to solve tasks based on CTsCALL.
- **Environmental-technology-fit (ETF):** the degree to which environmental characteristics of VE are suitable for solving language tasks through CTsCALL.

- **Intention to use (ITU):** the intention of language learners to use VE in the future.

2.3. Virtual exchange in language learning

Virtual exchange (VE) refers to a series of sustained interactions between student groups and international partners, facilitated by online technologies and guided by teachers. As previously noted, VE is considered a sub discipline of CALL and offers numerous benefits for language learning and cultural exchange. Advocates of VE emphasize its flexibility, as it can be integrated into teaching in various formats, including in-class or hybrid learning environments. In addition to providing students with unique opportunities for social interaction and collaboration with peers, VE enables them to engage with participants they might not otherwise encounter in traditional educational settings. Furthermore, it serves as an alternative to physical mobility for students with disabilities or financial constraints, while promoting language practice and internationalization for all learners (Dooly & Vinagre, 2021).

A key distinction between VE and other language teaching methods is its reliance on connections between language teachers and students in different geographic locations. This necessitates the development and collaborative implementation of carefully designed tasks and activities. We chose VE as a context for cultivating CTsCALL due to its significant advantages over other language learning environments.

2.4. Hypotheses formulation

Recent studies have emphasized virtual exchanges and telecollaborative environments as effective means of enhancing students' language skills, 21st-century competences, and overall enjoyment. Scholars suggest that through experiential and task-based learning, learners develop problem-solving abilities and creativity (Ou Yang et al., 2023; Sevilla-Pavón & Nicolaou, 2020). For example, Ou Yang et al. (2023) found that augmented reality-based virtual exchanges (AR) enhanced learners' algorithmic thinking by providing feedback, which in turn improved their learning enjoyment and attitudes toward AR virtual exchange. Similarly, Demir and Kayaoğlu (2021) reported that virtual group exchanges were particularly effective for problem-solving activities, as participants collaborated, shared information, and developed step-by-step solutions to specific tasks. Furthermore, Ware and O'Dowd (2008) highlighted that analyzing and adapting cultural products in telecollaborative environments—where language learners collaborated, translated and adapted content—helped develop their intercultural competence. Recent findings (e.g., Demir & Kayaoğlu, 2021; Ou Yang et al., 2023) suggest that algorithmically solving language tasks and other activities in VE contexts enhances learners' cultural competence, enjoyment, and problem-solving skills. Based on these findings in the literature, we developed the following hypotheses:

•H1: solving virtual exchange tasks algorithmically positively predicts language learners' (H1a) task-technology-fit, (H1b) individual-technology-fit and (H1c) environmental-technology-fit.

In another study, Oakley et al. (2017) and colleagues examined an online exchange between Chinese and Australian language learners in which Australian language learners used Mandarin and Chinese language learners used English, and they exchanged language and cultural information via digital storytelling. As part of the exchange procedure, language learners were required to complete some tasks relating to traditional tales, which focused on key information and related it to their cultures. These exchanges contributed to developing language learners' digital literacy and attitudes toward continuing exchanges.

As part of another collaborative exchange with Vietnamese English as a Foreign Language (EFL) students, Nguyen et al. (2020) reported that language learners broke down language exercises into distinct parts that encompassed language communication, grammar, vocabulary, and pronunciation. Through the breakdown of such language exercises, students were able successfully negotiate an intercultural exchange and acquire 21st-century skills, such as innovation, and thinking skills. Similarly, O'Rourke (2007) reported that the collaborative writing passage in which language learners rewrote stories collaboratively by summarizing them required them to select the critical information of such passages collaboratively to improve their meta-linguistic awareness, accuracy, and fluency.

Tomanova et al. (2024) found that students with CT skills, particularly in abstraction, displayed more positive attitudes toward mathematics and performed better than those without these skills, indirectly highlighting the alignment between mathematics, CT and learners' skills. In another study, Boom and colleagues (2022) observed that abstraction was one of the most frequently used CT skills by computer programmers working with Scratch and visual programming. This skill also influenced their perception of program quality. Üşengül and Bahçeci (2020) conducted an experimental study in which one group received traditional science instruction, while the experimental group developed CT skills using LEGO WeDo 2.0 Robotic Education Sets. The authors reported that the experimental group felt more positive about learning STEM with WeDo 2.0, as they applied CT skills in the robotic environment. This demonstrated the fitness between CT, STEM education and the WeDo 2.0 robotic environment, which impacted students' performance and changed their overall perceptions of STEM education.

Building on these findings, language activities involving abstraction could significantly affect outcomes such as cultural awareness and language proficiency. Additionally, recent STEM studies have highlighted the role of abstraction in shaping learners' performance and attitudes toward mathematics learning and programming quality. Following this approach, we aim to investigate how abstraction can predict language learners' perceived fit with VE and their individual skills. Based on these insights, we propose the following hypotheses:

•H2a: solving virtual exchange tasks through abstraction positively predicts the language learners' (H2a) task-technology-fit, (H2b) individual-technology-fit and (H2c) environmental-technology-fit.

Virtual exchange is characterized by cooperative language learning and the exchange of languages between geographically-dispersed students from two or more classes and two or more cultures. Several recent studies about virtual exchange demonstrated the significant influence of collaborative language tasks on the development of learners' creativity, ICC and motivation (Demir & Kayaoğlu, 2021), 21st-century skills (Nguyen et al., 2020), 21st-century digital competence (Sevilla-Pavón & Nicolaou, 2020), and overall positive perceptions (Luo & Yang, 2021). Moreover, STEM studies have highlighted problem-solving collaboration as a crucial CT skill, linked to higher learning performance and more positive attitudes toward the subject among STEM learners (Bounou et al., 2023; Lai et al., 2023; Lai & Wong, 2021). Research indicates that cooperative and collaborative language communities in VE, along with CT skills in STEM education, contribute to a variety of positive outcomes for both language and STEM learners. To explore how this CT skill may align with foreign language learners' abilities and the VE process, we developed the following hypotheses:

•H3: solving language tasks collaboratively positively predicts language learners' (H3a) task-technology-fit, (H3b) individual-technology-fit and (H3c) environmental-technology-fit.

Studies have shown that comparative and analytical language tasks in virtual exchange where language learners compared various solutions and searched for the most appropriate one positively impacted their cultural and psychological outcomes. Luo and Gao (2022), as well as O'Dowd and Ware (2009) report that, when learners answer language tasks by comparing and analyzing various texts, cultural products, and

stories, they become more aware of their own culture as well as the target culture. Additionally, other studies concluded that when language learners collaborated on language tasks such as answering grammar questions or choosing answers from various options for vocabulary, they developed their motivation (Demir & Kayaoğlu, 2021), creativity (Nguyen et al., 2020) and perception (Luo & Yang, 2021). On the basis of the previous findings, activities that required language learners to compared various responses and selected the most appropriate ones positively influenced their language outcomes and psychological well-being. However, they have not been examined in terms of their compatibility with the language learners' abilities and the VE environment. As a result of this gap and with a view towards addressing it, the researchers propose the following hypotheses:

•H4: solving language tasks through evaluation positively predicts language learners' (H4a) task-technology-fit, (H4b) individual-technology-fit, and (H4c) environmental-technology-fit.

Without a doubt, the primary objective of any CALL material is to enable students to acquire a language and use it effectively in the target context (Rahimi, 2023). According to Bueno-Alastuey and Kleban (2014), some participants had positive attitudes toward VE, enabling them to express themselves confidently when speaking with participants from the target environment, which come from the patterns recognitions they achieved in their VE. The community of practice nature of VE has been found to motivate learners to develop their cultural awareness, and to engage in more personal and local exchanges in their live experiences (Sevilla-Pavón & Nicolaou, 2020; Wu & Miller, 2019). Furthermore, studies have shown that language learners have a greater sense of competence within the target language context by participating in telecollaborations in Second Life 3D virtual environments, reducing speaking anxiety and increasing positive attitudes toward interaction in real-life situations. (Chen & Sevilla-Pavón, 2023; Wang & Kartika Sari, 2023). Moreover, Kohn and Hoffstaedter (2017) provided evidence that VE fostered language learners' agency in relation to the target context and communication, which are essential elements of real-life situations.

Several studies suggest that STEM learners are particularly adept at interpreting learning patterns and models, designing and implementing algorithms to solve programming problems, and applying these algorithms to new challenges (Boom et al., 2022; Bounou et al., 2023; Falloon, 2024). This indicates that the generalizability aspect of CT is being used in ways that align with their skills and STEM tasks. However, in the context of language learning (VE and CALL), the alignment between pattern recognition skills based on CTsCALL and learners' abilities, as well as the fit with the VE environment and tasks, has not been thoroughly explored. To address this gap, the researchers developed the following hypotheses.

•H5: the generalization features of language tasks in telecollaboration positively shapes language learners'(H5a) task-technology-fit, (H5b) individual-technology-fit, and (H5c) environmental-technology-fit.

Building on the TTF framework, it is posited that the ability of technology to support tasks increases the likelihood of its use, thereby positively influencing users' intentions to continue using the technology (Goodhue & Thompson, 1995). Recent studies further emphasize that, in addition to the alignment between target technology and learners' capabilities, the tasks provided by the technology are also key predictors of learners' intention to use it. This has been explored in various learning environments, including virtual learning environments (Zhang et al., 2017), MOOCs (Wan et al., 2020), and online learning (Liu et al., 2023). Additionally, previous research has highlighted the role of mediators, such as task-technology fit, individual-technology fit and environmental-technology fit, in influencing learners' intentions to use target technology (Alyoussef, 2021; Isaac et al., 2019; Lu and Yang, 2014). Based on these insights, the following hypotheses were developed:

- H6a: the task-technology-fit will positively predict learners' intention to use virtual exchange in the future.
- H6b: the individual-technology-fit will positively predict learners' intention to use virtual exchange in the future.
- H6c: the environmental-technology-fit will positively predict learners' intention to use virtual exchange in the future.
- H7: the task-technology fit will positively mediate the relationship between language learners' abstraction (H7a), algorithmic thinking (H7b), collaboration (H7c), generalization (H7d), and evaluation skills (H7e), and their intention to use VE.
- H8: the individual-technology fit will positively mediate the relationship between language learners' abstraction (H8a), algorithmic thinking (H8b), collaboration (H8c), generalization (H8d), and evaluation skills (H8e), and their intention to use VE.
- H9: the environmental-technology fit will positively mediate the relationship between language learners' abstraction (H9a), algorithmic thinking (H9b), collaboration (H9c), generalization (H9d), and evaluation skills (H9e), and their intention to use VE.

2.5. Literature gap, study aim and conceptual model

A review of recent literature has highlighted the significant contribution of VE to the development of language learners' ICC, motivation, perceptions and creativity. However, our review also revealed that recent studies have primarily focused on language skills and subskills, with limited attention to language learners' 21st-century digital skills, particularly CT skills. While some studies have indirectly addressed skills such as abstraction (Nguyen et al., 2020), evaluation (Demir & Kayaoğlu, 2021) and collaboration (Bounou et al., 2023), none have simultaneously applied these skills under the framework of CTsCALL. This gap led us to develop the CTsCALL framework and validate its factorial structure within this research area.

Furthermore, studies have demonstrated that CT can positively influence learners' performance and attitudes toward STEM subjects and the learning environment in general. However, no study has simultaneously examined the fit of CT with learners' skills, tasks or the target environment (Üşengül & Bahçeci, 2020). To address this, we explored whether CT is compatible with students' individual skills, the VE environment and the tasks within VE. Our literature review also revealed a gap in research regarding whether language learners have behavioral intentions to continue learning a language or engage in cultural exchange within the VE context. The importance of this continued intention lies in understanding each CALL user's attitude toward using CALL materials, as noted by Rahimi (2023).

Moreover, according to the dynamic systems theory, language learners' psychological factors interact both independently and cooperatively in any language learning context, and these behaviors are context-specific (Freeborn et al., 2022; Larsen-Freeman & Cameron, 2008; Rahimi, 2023; Rahimi & Sevilla-Pavón, 2025). This insight prompted us to explore the serial correlation between CTsCALL, TTF and learners' intention to use VE (ITU).

Our literature review also revealed that recent studies have primarily focused on the process of learning a language or fostering cultural awareness within VE (O'Dowd, 2021). While these studies have concentrated on the outcomes of language learners, our research extends this focus by considering not only the language learning process (problem-solving-oriented CTsCALL) but also the intentions to continue using VE. Additionally, the mediation roles of task-technology fit, individual-technology fit, and environmental-technology fit have been explored in MOOCs and other digital learning environments with predictor variables like perceived ease of use (Alyoussef, 2021), system quality (Klassen, Wang, & Rushby, 2023), and social characteristics (Lu and Yang, 2014). However, their role as mediators between language

learners' CTsCALL and their intentions to use VE has not been examined, prompting us to explore this aspect.

Finally, our review revealed that most studies in this field rely on qualitative or quantitative research designs following sufficiency logic (Boom et al., 2022; Bounou et al., 2023; Falloon, 2024). This led us to adopt fsQCA, following necessary logic, to identify the core and peripheral conditions influencing learners' intention to use VE. Based on these findings, we propose the following model hypothesis:

3. Methodology

3.1. Virtual exchange procedures, tasks and study context

The data for this study comes from two distinct partnerships designed and facilitated by the second author. These involved the collaboration among Spanish students from the university of Valencia with either Cypriot or Irish students during one semester in either English lingua franca or L1 Spanish-English tandem settings.

Through VE, language learners were able to apply CTsCALL across various tasks. To clarify algorithmic thinking skills, the second author guided students step-by-step when solving their tasks. This approach emphasized the importance of successfully completing one task in order to progress to the next and eventually complete the course. In the initial phase, students engaged in ice-breaking activities by asking each other general questions, exchanging self-introductory videos, and playing games and other introductory activities focused on the target cultures.

Following this, students used their abstract thinking skills to exchange cultural items. They read excerpts from novels and watched short film clips about famous characters (e.g., Robin Hood). They analyzed the political themes behind these characters' traits and explored the anachronisms between various portrayals of these characters and their historical context. Once students reached a consensus and collaboratively made their decisions, they submitted a joint report and prepared interview questions.

Regarding evaluation skills, students were asked to evaluate multiple responses and select the most accurate ones. This was done through several multiple-choice questions based on their exchanges in a virtual reality museum, which included references to the target cultures (Fig. 4). Additionally, students engaged in brainstorming sessions to approach different tasks. The task required the co-construction of a final artifact, which emerged from a collaborative exploration of their cultural, historical, and geographical differences and similarities. This artifact, created creatively by blending written information, images, and student-produced video clips, served as an integral part of their project (Fig. 2).

Generalization skills were evident during social theater improv games and exercises (Amador & Liossis, 2023), which centered on Robin Hood and other historical figures and events the students had previously researched. In preparation for their final project—creating digital stories—these activities helped students incorporate ideas into their scripts. They role-played different characters, reflecting on their personalities, political behaviors, and historical relevance. This demonstrated their ability to recognize patterns in literature and cultural texts and to transform them using multimodal strategies.

By interacting in the dedicated Museum room on Spatial (which featured cultural items from all three countries) and using the AI platform HelloHistory, students were able to explore cultural differences and similarities. This collaborative exploration occurred as they moved from station to station along a learning path. Through this process, they developed a collaborative discovery process (collaboration skills) and brought together various media types, including written texts, images, and video clips.

Moreover, through intercultural exploration, students solved tasks by applying algorithmic thinking and evaluation skills. They worked step-by-step, implementing their ideas collaboratively to create final digital stories about the creation of a new country or an interview with a historical figure. The success of their final products depended on both their technical correctness and their appeal to other project participants.

In the final steps, students summarized their knowledge and insights about the target cultures (abstraction skills) and reflected on different cultural aspects that could be valuable in other contexts—such as within the context of their newly-created country. Students also answered multiple-choice questions to evaluate their understanding (evaluation skills).

Table 1 outlines the VE CTsCALL timeline procedure, while Fig. 1, to 5 in the supplementary materials provide examples of the various CT skills and VE tasks from our project.

After the VE, we used a simple non-probability sampling method to select our Spanish participants and asked them to complete the study scale. This approach ensured that all participants had an equal and independent opportunity to take part in the study (Ary et al., 2010). The majority of participants were female (70), while 22 were male. Most participants were aged between 22 and 26, with 22 participants under 18 and two older than 26. Table 2 presents participants' demographics information:

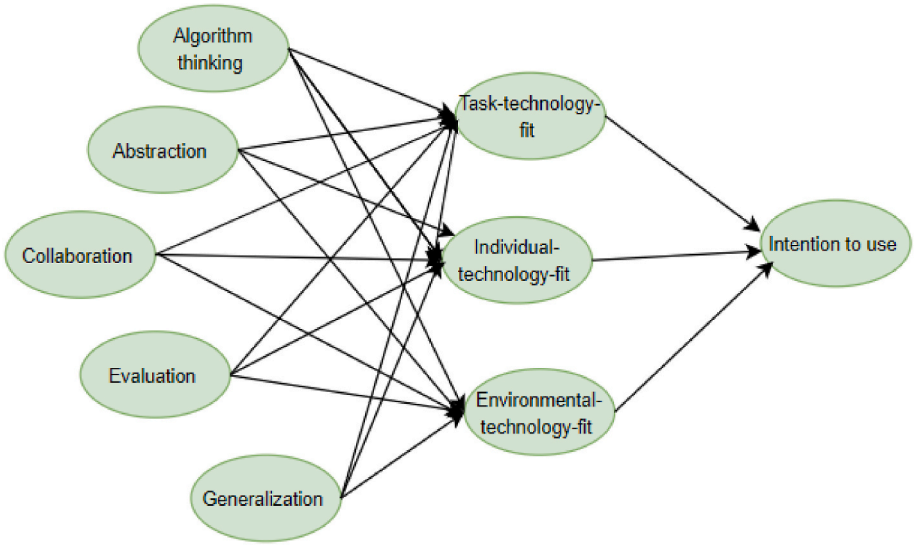

Fig. 1. The study hypothesized model.

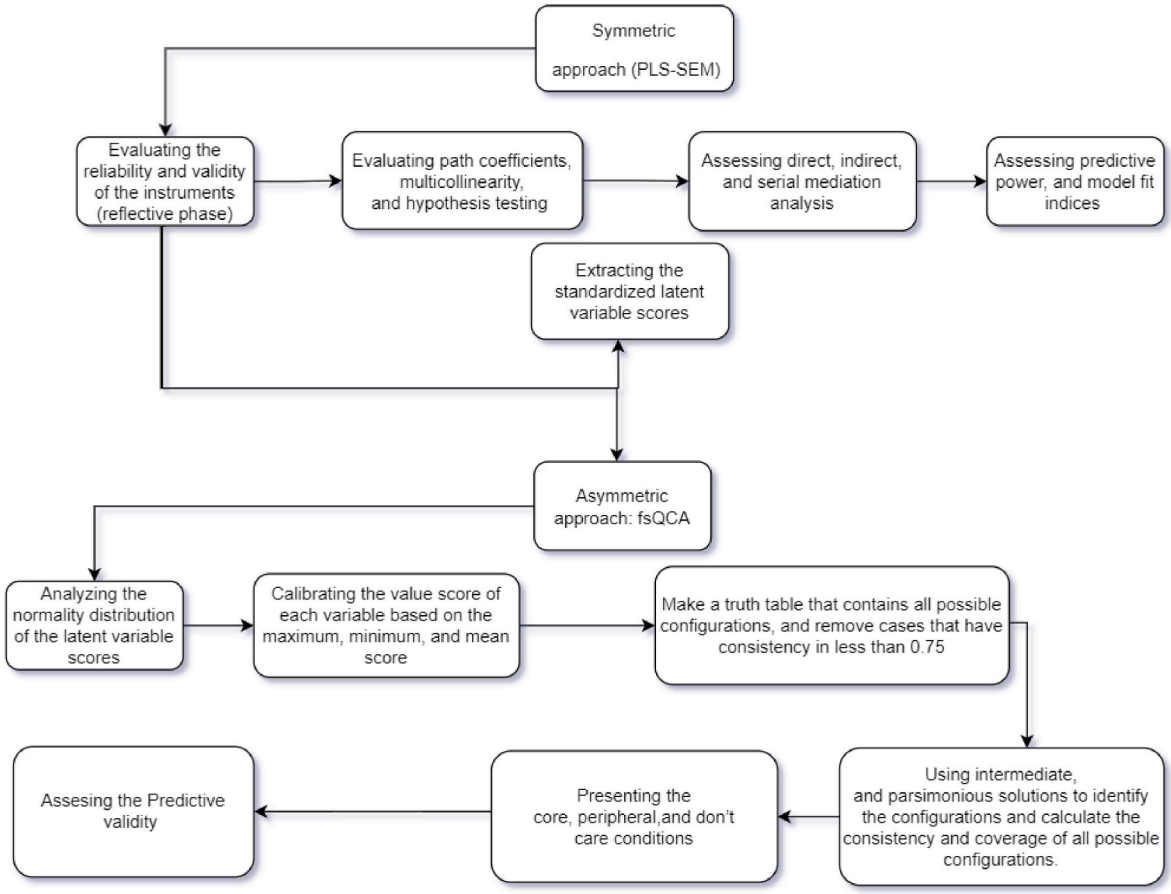

Fig. 2. The data analysis process.

3.2. Instrumentation

To develop the CTsCALL scale for the field of English language learning, and CALL, the authors followed the ten steps described by Slavec and Drnovšek (2012) within three phases: firstly, the researchers applied the deductive approach by reviewing the previous literature. We developed 37 items in this phase. Due to the heavy use of CT literature in STEM education and the creation of domains and items from our own perspectives, we needed an inductive approach to transform abstract concepts into concrete forms. Therefore, we interviewed 15 participants and recorded their interviews for further analysis to learn how they solved VE tasks. This ensured the researchers' conceptualizations of CT-matched learners were accurate. Using both deductive and inductive approaches, as well as editing and deleting items, we reached 24.

Expert judgment was applied to assess the content's validity, which included eight experts from CALL, applied linguistics, VE, and STEM education. We selected the Delphi methodology due to its proven effectiveness and superiority over traditional methods like focus groups (Almohanna et al., 2022), which allows participants to remain anonymous without expert pressure (Taylor, 2019). We used a web-based platform to share questionnaires, domain definitions, and items with experts. After three expert panel discussions, we analyzed their comments, applied them, and shared them again; at last, they agreed to a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Scale items also reached 15. We measured inter-rater agreement by sending them the scale and asking them to complete it, with 1 representing slight agreement and 5 representing full agreement. Krippendorff's alpha value was used to assess inter-rater agreement, and it exceeded 0.8, indicating high expert agreement in the final scale version.

Taking into account the importance of determining whether respondents, end users, and lay respondents find the items relevant and meaningful, we assessed face validity with a cognitive interview (Willis, 2004). It allows us to evaluate if the items will produce the desired data without confusion or difficulty understanding (Balza et al., 2022). Therefore, we invited eight participants who closely resembled the target population. We gave them a draft survey question and conducted interviews to gauge their understanding. Two rounds of interviews led to minor revisions to the items. This scale was then piloted on 242 participants who had similar characteristics to our participants. Accordingly, 20 percent (N = 50) of these participants were between 18 and 20, 77.3 percent (N = 187) were between 20 and 22, and the remaining participants were over 22, all with one to two years of virtual exchange experience. With this number of participants, we followed Hair et al.'s (2014) recommendation of five observations for each variable to evaluate its psychometric properties.

Following the collection of data, the scale items were dimensionally assessed using exploratory factor analysis (EFA). This is accomplished by measuring Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity test. A KMO value greater than 0.50 indicates that the data set is suitable for factor analysis. The Bartlett value obtained was below 0.85 and therefore, it rejected the zero hypothesis at the meaningfulness level of 0.05. After that, principal component analysis and varimax steep rotation were applied as factorization techniques. Factor analysis can be used to determine whether items on a scale are distributed among fewer factors or not. Accordingly, factor loads of less than 0.5 and initial eigenvalues of less than 1 should be excluded from the questionnaire. In Table 3, all five CTsCALL's factor loadings exceeded 0.5, and their initial Eigenvalues exceeded 1. Furthermore, the factor loads of the items on the scale explain 75.90% of the variance, which is considered sufficient in a

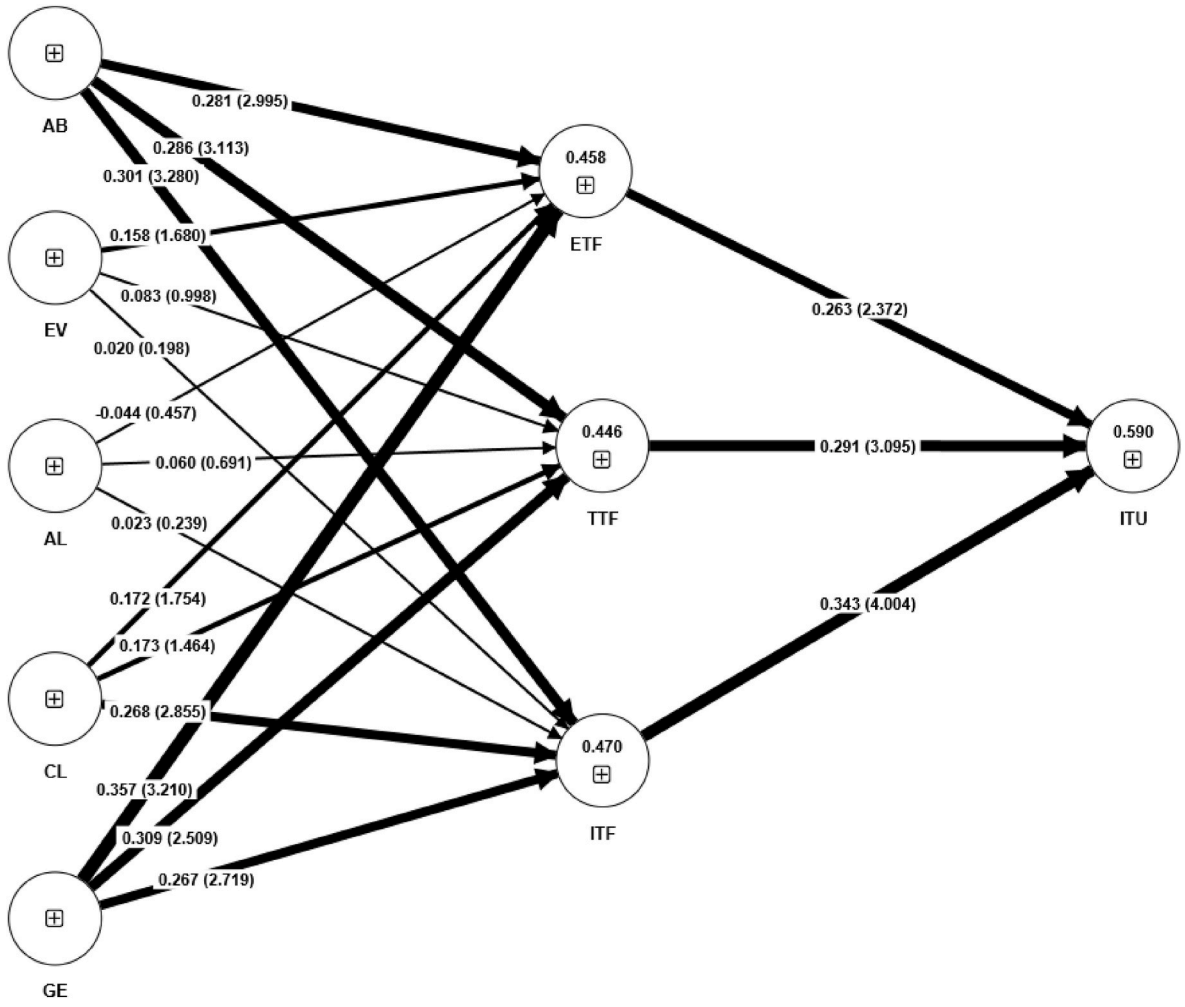

Fig. 3. Final model with relative value.

humanistic field. This scale had a total reliability of 0.88, above the 0.70 threshold.

We used confirmatory factor analysis (CFA) with Analysis of Moment Structure (AMOS.26) to check CTsCALL internal consistency, convergent validity, and discriminant validity. As shown by CFA composite reliability (CR) exceeded 0.7. Average variance and maximum squared variance (MSV) were used for convergent validity, and both were obtained below the average shared variance (ASV). Moreover, all the AVE values were above 0.5. Table 1 in supplementary files shows convergent validity and internal consistency of the study.

The discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT), which is a measure of whether a construct is empirically distinct from others if their roots of average square are above 0.85 (Henseler, Ringle, & Sarstedt, 2015), as shown in Table 2 in the supplementary file.

Table 3 in supplementary material shows that the $\chi 2/df$ ratio was less than 2, the comparative fit index (CFI) and the Tucker Lewis index (TLI) were both above 90, and the root mean square error of approximation (RMSEA) was less than 0.6, showing that the CFA model fit well (Byrne, 2016).

After developing, and validating the CTsCALL, the researchers also adopted their task-technology from Goodhue and Thompson (1995) (e.g., 'I could independently, and cooperatively solve tasks in virtual exchange'), Individual-technology-fit, adapted from Wu and Chen (2017) (e.g., 'I tried to interact with others to solve tasks and performed well in virtual exchange'), environmental-technology-fit, adapted from Liu et al., (2023) (e.g., Virtual exchange provided a real-time problem-solving, and language exchange environment), and Intention to use, adapted from Lu and Yang (2014) (e.g., 'Once I have learned language or exchange cultural information in virtual exchange, I will continue to use it'). An appendix contains the study scale's normality distribution and sources. All the items were rated from 1 (strongly disagree) to 5 (strongly agree) and distributed normally between −1 and +1.

3.3. Study design and data analysis

The study adopts a bisymmetric approach by integrating symmetrical and asymmetrical approaches. Based on the null hypothesis significance test (NHST), the symmetric approach evaluates the direct correlation between two or more variables by using tools and mean-based data analysis techniques such as PLS-SEM, while asymmetrical data analysis, combines the logic and empirical intensity of qualitative approaches with quantitative methods that are more generalizable and applicable to large numbers of instances (Pappas & Woodside, 2021; Rahimi & Sevilla-Pavón, 2024b). Therefore, they are not reliant on NHST but rather on configurations. A configuration is a combination of casual variables used to assess outcomes. For clarification, language learners' learning achievements with various language learning experiences, skills, and styles might not be represented by the one-model-fits-all produced from the standard regression approaches or analysis of variances (ANOVA) which provides a single explanation for the outcome by examining the net effects among variables. The focus on net effects may, however, be misleading since, in the real world, the

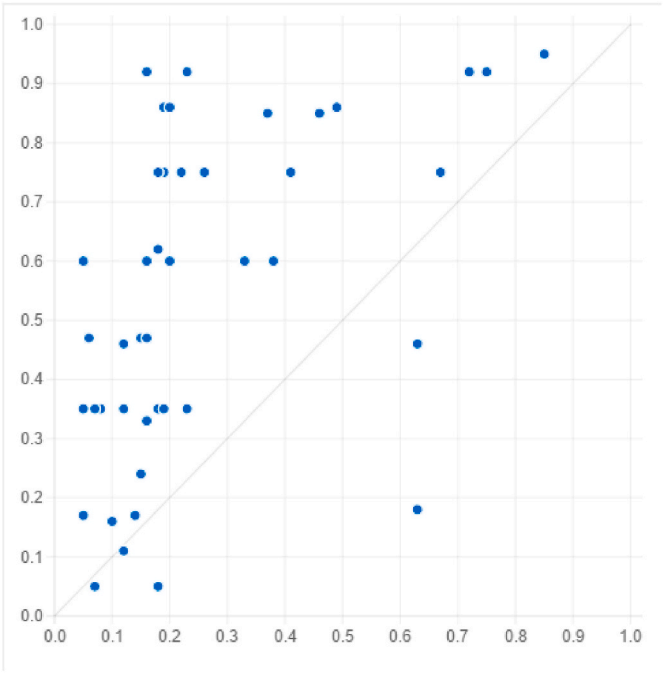

Fig. 4. The XY plots for sufficient configurations to predict IU based on sub-sample 2.

opposite relationship is often found between the same variables within a particular sample (Woodside, 2013). As a result, various configurations of the variables examined may result in the same outcome. Consequently, such configurations result in multiple solutions, which together represent a substantial percentage of the sample and which may account for a large percentage of the results, depending on how they combine.

Six factors led us to choose PLS-SEM for the symmetric part of our data analysis. Ordinarily least squares and principal component analysis were combined in PLS-SEM to make weighted composites and test them in a planned way (Ringle et al., 2023). Additionally, PLS-SEM has a strong focus on theory development since this statistical method is predictive in nature, particularly with a low number of participants (Hair et al., 2021); thirdly, PLS-SEM does not exhibit any sensitivity to normality distributions and can evaluate the complex relationship with low number of participants (Hair et al., 2021). Furthermore, it could evaluate both moderation and mediation effects simultaneously (Hair et al., 2021). In addition, it is possible to implement higher-order constructs in PLS-SEM, which allows for the specification of a construct at multiple levels of abstraction simultaneously (Sarstedt, Hair, Nitzl, Ringle, & Howard, 2020). However, although recent studies in VE have extensively utilized case studies (Ware & O'Dowd, 2008), comparative methods (Chen et al., 2013), and action research (Luo & Gui, 2019), to the best of our knowledge, none of the CALL researchers have tended to develop or test a theory in this context.

Furthermore, we applied fuzzy-set qualitative comparative analysis as a systematic approach to the study, which extended the Crisp-Set Qualitative Comparative Analysis (csQCA) by integrating fuzzy logic and fuzzy set principles (Pappas & Woodside, 2021). Using both fsQCA and PLS-SEM together could give more nuanced results and information about the study hypotheses. It could also help judge the predictive power of a model based on logical and theoretical principles within the limits of a carefully constructed model (Chin et al., 2020). Fig. 2 provides a detailed description of the study design.

Table 1
CTsCALL VE activities and timeline.

Week	Activities	CT Skills
Week 1	Ice-breaking activities: asking general questions, exchanging self-introductory videos, playing games, and completing cultural activities.	**Collaboration**: cooperate in introductory activities and exchange ideas. **Algorithmic Thinking**: step-by-step process in creating profiles and videos.
Week 2	Exchanging cultural items, reading excerpts from novels, watching short film clips about historical characters, analyzing political themes and historical context.	**Abstraction**: focus on the main ideas behind the political themes and the historical context. **Generalization**: recognize patterns in cultural representations.
Week 3	Collaborative decision-making to submit a joint report and prepare interview questions.	**Collaboration**: work together to form ideas, write reports, and prepare interviews. **Evaluation**: evaluate the significance of cultural items.
Week 4	Participating in virtual reality museum activities: exploring target cultures, responding to multiple-choice questions connected to the target culture.	**Evaluation**: selecting the most accurate answers from multiple options in virtual museum exchanges.
Week 5	Brainstorming sessions to develop approaches to the project tasks, including group work for co-constructing the final artifact.	**Collaboration**: co-constructing the artifact through cooperative exploration and task-sharing.
Week 6	Creating a final artifact blending written information, images, and video clips.	**Generalization**: applying learned concepts to create a cohesive final artifact. **Abstraction**: summarizing key ideas to produce final content.
Week 7	Social theater improv games and exercises on different historical figures as a way of generating ideas for the script and final digital stories.	**Generalization**: recognizing patterns in historical contexts and applying them to the script. **Collaboration**: working together to perform and discuss characters.
Week 8	Role-playing characters from historical contexts, reflecting on their personalities, political behaviors, and historical relevance.	**Generalization**: recognizing patterns in historical and literary characters. **Abstraction**: simplifying complex character traits for role-play.
Week 9	Developing final digital stories about a new country or a historical figure after conducting AI-supported interviews in HelloHistory.	**Algorithmic Thinking**: organizing and structuring content step-by-step to develop the digital story. **Evaluation**: reviewing and assessing content for accuracy and relevance.
Week 10	Collaborative exploration of cultural items in Spatial.	**Collaboration**: working together to explore cultural artifacts in a virtual reality space. **Algorithmic Thinking**: sequential exploration and task completion.
Week 11	Final digital story presentation, emphasizing both technical correctness and appeal to project participants.	**Algorithmic Thinking**: following a structured approach to finalize the digital story. **Evaluation**: assessing the technical and creative aspects of the project.
Week 12	Reflecting on cultural aspects and finalizing knowledge about target cultures. Answering questions for evaluation.	**Abstraction**: summarizing insights gained from the project and simplifying complex ideas. **Evaluation**: reviewing and selecting the most appropriate answers based on the acquired knowledge.

4. Results

4.1. Reflective model

We evaluate factor loading, reliability, and convergence validity in the PLS-SEM's reflective model. Reliability was measured by Cronbach's

Table 2
Participants' demographic information.

		N	%
Gender	Male	22	23.9
	Female	70	76.1
	Years		
Age	>18	20	21.7
	22–26	70	76.1
	26<	2	2.2
	Years		
Language	1–2	2	2.2
Learning	3–5	52	56.5
Experience	5<	38	41.3

alpha and composite reliability. For all of them, Hair et al. (2021) recommend a value above 0.70. For convergent validity, we used the average variance extracted (AVE), which should be greater than 0.5. Based on Table 4, all latent variables were valid and reliable.

Additionally, we evaluated the discriminant validity of latent variables based on Fornell and Larker's 1981 criteria, and as shown in Table 5, that variable's roots showed a higher correlation with itself than with other variables.

4.1.1. The formative model

The formative model evaluation includes various metrics incorporating multicolinerarity, path coefficient effect size, coefficient of determination (R^2), Stone-Geisser's (Q^2) value; (Geisser, 1974), and, Standardized Root Mean Square Residual (SRMR). We measured the variance inflation factor (VIF), which is under 5 for all endogenous variables (Hair et al., 2021). Moreover, we have analyzed the direct path coefficients of the hypotheses to answer the second research question. As shown in Table 6, the results support H2a (β = 0.286;), H2b (β = 0.301), H2c (β = 0.281), H3a (β = 0.173), H3b (β = 0.268), H5a (β = 0.083), H5b (β = 0.267), H5c (β = 0.357), H6a(β = 0.291), H6b (β0.343), H6c (β = 0.263) of study hypotheses. The rest had t-values below 1.96 or p-values above 0.05, rejecting study hypotheses.

A bootstrap analysis with 5000 subsamples and 97.5 % Confidence Intervals (CI) was conducted to determine the direct effects of CTsCALL on BI. Table 7 shows that abstraction (β = 0.260), collaboration (β = 0.187), and generalization (β = 0.275) significantly predicted BI. Meanwhile, the remaining CTsCALL failed to predict it.

By running bootstrap indirect analysis with 5000 subsamples and 97.5 % CI we will answer the third research question. As presented in Table 8 TTF significantly mediated the relationship between generalization (GE > TTF > ITU; β = 0.090) and abstraction (AB > TTF > ITU; β = 0.090) with ITU. Similarly, ITF significantly mediated generalization (β = 0.091), abstraction (β = 0.103), collaboration (β = 0.092), with ITU. Thus, the task-technology-fit, and individual technology fit were the only mediator variables of the TTF framework, that mediate the relationship between learners' CTsCALL, and their intentions to use VE.

Additionally, the variance grafted between exogenous and endogenous constructs is calculated with in-sample predictive power. As a general rule, 0.19, 0.37, and 0.067 indicate weak, moderate, and strong predictive power (Hair et al., 2021). The coefficients of determination of CTsCALL predicted and changed 45% of EFT, 47% of ITF, 44% of TTF, and 59% of ITTEF. Fig. 3 also highlighted its paths whose variables contributed to change and predict target variables' R^2 in the model.

Moreover, we estimated a Stone-Geisser's (Q^2) value to gauge the model's accuracy, and all values were above 0. SRMR also yielded a model fit index that was obtained below 0.08 (Table 9).

4.2. Asymmetric analysis: fuzzy-set qualitative comparative analysis (fsQCA)

We used fsQCA to investigate how the combination of CTsCALL and three mediators influences language learners' ITU toward VE. The first step was to export latent variable scores from the measurement analysis to the fsQCA and calculate their normality distribution. Table 10 demonstrates the normal distribution of the latent variable scores.

Table 4
Research construct reliability and convergent validity.

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AB	0.911	0.912	0.944	0.848
AL	0.891	0.897	0.932	0.820
CL	0.866	0.868	0.918	0.788
ETF	0.780	0.781	0.872	0.695
EV	0.811	0.831	0.886	0.722
GE	0.901	0.903	0.938	0.834
ITF	0.819	0.820	0.892	0.734
ITU	0.828	0.835	0.897	0.744
TTF	0.853	0.855	0.910	0.772

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

Table 3
Result of the exploratory factor analysis.

Factors	Factors					
	Algorithmic thinking	Evolution	Abstraction	Collaboration	Generalization	Extraction
Algorithmic thinking 1	**0.828**	0.045	0.164	0.231	0.154	0.792
Algorithmic thinking 2	**0.847**	0.119	0.073	0.141	0.091	0.765
Algorithmic thinking 3	**0.837**	0.073	0.158	0.151	0.172	0.783
Evaluation 1	0.079	**0.807**	0.187	0.188	0.098	0.737
Evaluation 2	0.056	**0.868**	0.122	0.098	0.142	0.801
Evaluation 3	0.099	**0.853**	0.084	0.097	0.132	0.771
Abstraction 1	0.154	0.132	**0.806**	0.149	0.170	0.741
Abstraction 2	0.157	0.113	**0.818**	0.126	0.169	0.752
Abstraction 3	0.074	0.144	**0.822**	0.095	0.106	0.722
Collaboration 1	0.170	0.187	0.141	0.241	**0.779**	0.748
Collaboration 2	0.161	0.103	0.154	0.134	**0.827**	0.762
Collaboration 3	0.098	0.122	0.172	0.210	**0.787**	0.717
Generalization 1	0.139	0.167	0.158	**0.819**	0.202	0.783
Generalization 2	0.300	0.125	0.196	**0.766**	0.157	0.755
Generalization 3	0.155	0.132	0.067	**0.809**	0.239	0.757
Initial Eigenvalues	5.77	1.79	1.43	1.33	1.05	
Percentage variance explained	38.49	11.93	9.57	8.87	7.034	
Percentage variance Cumulative	38.49	50.42	59.99	68.87	75.90	

Table 5
Result of the discriminant validity.

AB	0.913							
AL	0.358	0.906						
CL	0.662	0.340	0.888					
ETF	0.567	0.298	0.526	0.833				
EV	0.050	0.187	0.153	0.252	0.850			
GE	0.368	0.447	0.385	0.491	0.204	0.921		
ITF	0.564	0.348	0.571	0.663	0.140	0.516	0.857	
ITU	0.510	0.308	0.416	0.682	0.256	0.559	0.661	0.862
TTF	0.554	0.373	0.521	0.660	0.195	0.510	0.496	0.634	0.879

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

Table 6
Results of the study hypotheses.

Research hypothesis	Path exogenous ——— > endogenous	t-value	β	p-value	VIF	Remark
H1a	AL > TTF	0.69	0.060	0.480	1.34	Rejected
H1b	AL > ITF	0.23	0.023	0.811	1.34	Rejected
H1c	AL > ETF	0.58	−0.044	0.647	1.34	Rejected
H2a	AB > TTF	3.11	0.286	0.002	1.39	Accepted
H2b	AB > ITF	3.28	0.301	0.010	1.39	Accepted
H2c	AB > ETF	2.99	0.281	0.003	1.39	Accepted
H3a	CL > TTF	2.76	0.173	0.000	1.89	Accepted
H3b	CL > ITF	2.55	0.268	0.016	1.89	Accepted
H3c	CL > ETF	1.75	0.172	0.080	1.89	Rejected
H4a	EV > TTF	0.99	0.077	0.318	1.07	Rejected
H4b	EV > ITF	0.19	0.020	0.843	1.07	Rejected
H4c	EV > ETF	1.68	0.158	0.084	1.07	Rejected
H5a	GE > TTF	2.50	0.083	0.001	1.88	Accepted
H5b	GE > ITF	2.71	0.267	0.007	1.88	Accepted
H5c	GE > ETF	3.21	0.357	0.001	1.88	Accepted
H6a	TTF > ITU	2.17	0.291	0.036	1.79	Accepted
H6b	ITF > ITU	3.00	0.343	0.006	2.41	Accepted
H6c	ETF > ITU	4.61	0.263	0.000	2.41	Accepted

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

Table 7
Result of the bootstrap direct analysis.

Path	β	2.5%	97.5%	t-value	p-value
AB > ITU	0.260	0.135	0.395	3.955	0.000
AL- > ITU	0.014	−0.103	0.134	0.232	0.816
CL > ITU	0.187	0.060	0.310	2.943	0.003
EV > ITU	0.073	−0.044	0.195	1.187	0.235
GE > ITU	0.275	0.136	0.404	4.024	0.000

4.2.1. Calibrating the data

After setting the outcomes and predictors, we calibrated our data to fuzzy sets. Fuzzy membership scores and calibration are among the most critical aspects of the fsQCA, so researchers should calibrate their fuzzy sets qualitatively since variations in calibration can affect results. For membership in the full set, non-membership, and intermediate set, three values are recommended (Ragin, 2006). Based on the survey's Likert scale, the researchers recommended rescaling membership. Based on Rasoolimanesh et al.'s (2021) recommendations, we calibrated our latent variable scores based on their maximum, minimum, and mean values.

The truth value table of fsQCA illustrates our calibration results by showing possible configurations to achieve the desired results. The fsQCA algorithm generates a truth table with 2k rows, where k represents the number of independent variables and each row signifies a potential combination (Mikalef & Pateli, 2017). As instances, a truth table between three variables provides six possible logical combinations. As well, a truth table showing conversion between fuzzy sets and configurations, along with a consistency score, are calculated to determine the reliability with which a variable combination results in a particular outcome (Papert, 1993). In addition, we removed cases with consistency below 0.75 (Pappas & Woodside, 2021). Table 11 represents our variables' truth table values.

4.2.2. The configuration analysis and fsQCA results

In the next step, it is necessary to check the frequency, coverage, and cut-off value of all configurations. Frequency describes each possible combination of observations. A cut point of 1 is appropriate for a small, and minimum sample. The next metric is consistency, which displays "the degree to which cases correspond to the set-theoretic relationships expressed in a solution" (Fiss, 2011; as cited in Papert, 1993. P. 9). It is recommended that consistency values be at least greater than 0.75 (Papert, 1993), and their raw coverage is above 0.20 (Fiss, 2011).

The raw coverage demonstrates how well the target solutions cover the outcome. In fsQCA, a solution is a set of conditions that lead to an outcome. Through traditional logic operations, complex solutions display all possible conditions. Consequently, it generates a wide range of conditions with several possible configurations, making interpretation difficult. For this reason, the researchers recommend using intermediate solutions, as reported in the article (Rasoolimanesh et al., 2021). By simplifying assumptions and providing essential conditions, a parsimonious solution is a simplified version of a complex solution. The intermediate solution strikes a balance between complex and parsimonious solutions.

Fiss (2011) recommends interpreting fsQCA results using a combination of parsimonious and intermediate solutions. Thus, we create a table with both core and peripheral conditions. The core conditions are the most important conditions that cannot be ignored in the solutions and belong to both parsimonious solutions and an intermediate one. Peripheral conditions refer to conditions that are associated with the intermediate solution but not with the parsimonious solution; a "do not care" condition refers to a situation in which the presence or absence of a condition does not predict the outcome (Pappas & Woodside, 2021). Therefore, we specified the conditions of the parsimonious solution in the intermediate solution. We also present a complete consistency and coverage of the solutions. A comparison of the R-square for regression-based methods and configuration-based methods can determine the overall coverage.

Results in Table 12 showed that CTsCALL variables were present in all solutions, while ITTF antecedents were absent in 9, 10, and 11. This highlights CTsCALL's beneficial effects on participants' ITU toward VE without three mediators. Further, from solutions 1 to 5, the CTsCALL had core conditions necessary for forming students' ITU toward VE (a necessary condition). It should be noted that by combining all the CTsCALL factors with the ITF and TTF, a high level of intention is obtained (solution 1). The learners' intentions to use VE were influenced by a combination of factors without abstraction or environmental fit

Table 8
Serial mediation analysis.

Hypothesizes	Path	β	2.5%	97.5%	t-value	p-value	Result
H7a	AB > TTF > ITU	0.083	0.017	0.173	2.047	0.041	Accepted
H7b	AL > TTF > ITU	0.018	−0.033	0.073	0.647	0.518	Rejected
H7c	CL > TTF > ITU	0.050	−0.016	0.140	1.249	0.212	Rejected
H7d	GE > TTF > ITU	0.090	0.012	0.187	1.973	0.049	Accepted
H7e	EV > TTF > ITU	0.024	−0.018	0.094	0.839	0.402	Rejected
H8a	AB > ETF > ITU	0.074	0.004	0.173	1.670	0.095	Rejected
H8b	AL > ETF > ITU	0.012	−0.069	0.044	0.430	0.667	Rejected
H8c	CL > ETF > ITU	0.045	−0.008	0.111	1.498	0.134	Rejected
H8d	GE > ETF > ITU	0.094	0.005	0.196	1.905	0.057	Rejected
H8e	EV > ETF > ITU	0.042	−0.009	0.113	1.327	0.185	Rejected
H9a	AB > ITF > ITU	0.103	0.031	0.195	2.435	0.015	Accepted
H9b	AL > ITF > ITU	0.008	−0.064	0.073	0.233	0.816	Rejected
H9c	CL > ITF > ITU	0.092	0.023	0.186	2.210	0.027	Accepted
H9d	GE > ITF > ITU	0.091	0.023	0.190	2.134	0.033	Accepted
H9e	EV > ITF > ITU	0.007	−0.061	0.088	0.185	0.853	Rejected

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

Table 9
Result of the structural model.

Variables	Q^2	R^2
ETF	0.296	0.458
ITF	0.302	0.470
TTF	0.281	0.446
ITU	0.419	0.590
Goodness of Fit Index $(GOF) = \sqrt{\overline{Communalities} \times \overline{R^2}} = \sqrt{0.878 \times 0.491} = 0.656$		
SRMR = 0.05		

Table 10
The latent variables scores' normality distributions.

	Mean	Excess Kurtosis	Skewness
AB	0.0000543478	−0.675	−0.502
AL	0.0000543478	−0.633	−0.257
CL	0.000076087	−0.571	−0.251
ETF	0.0000434783	−0.53	−0.312
EV	−0.0000978261	−0.013	−0.401
GE	0.0000434783	−1.01	0.123
ITF	−0.000119565	0.293	−0.453
ITU	−0.0000326087	−0.069	−0.412
TTF	−0.000141304	−0.906	−0.295

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

(solution 2), algorithmic thinking and abstraction (solution 3), generalization and algorithmic thinking (solution 4), collaboration and task fit (solution 5), evaluation, generalization, and algorithmic thinking (solution 6). Moreover, of all the solutions, the seventh included abstraction collaboration, algorithmic thinking, individual-task fit, and task-technology fit, and the eighth, which combined abstraction collaboration, algorithmic thinking, individual fit, and environmental fit, achieved the highest levels of coverage (0.552 and 0.557). The sole contribution of collaboration as a peripheral condition was also intriguing for three solutions (9, 10, and 11) to shape language learners' intentions to use VE.

In total, sixteen solutions shaped language learners' continued intentions toward VE, ranging from 21% to 55% of cases associated with outcome. Furthermore, all sixteen solutions account for 81% of the language learners' intention to use VE in the future.

4.2.3. The predictive validity

To determine whether we can predict the same dependent variable equally well on another sample, we examine the predictive validity of our results on a different sample (Papert, 1993). We randomly divided our samples into two sub-samples. In order to identify sufficient configurations, we used subsample 1 to identify those with a consistency greater than 0.8 and a coverage greater than 0.2 as recommended by (Papert, 1993). Based on subsample 1, Table 13 shows 14 configurations generating high levels of intentions towards VE with the high level of coverage and consistency.

By computing presence or absence conditions in the second subsample, every configuration in the first subsample was modeled as a single variable. A plot was then constructed against the outcome. They all met the consistency and coverage threshold. As shown in Fig. 4, almost half of the bottom right quarter of the Y plot is empty, which exceeds the sufficiency as addressed by Woodside (2013).

5. Discussion

5.1. The factorial structures of CTsCALL and ITTEF

The first research question was answered, and CTsCALL with five factors has been validated. Despite the claims of some STEM researchers that CT specializes in STEM education (Israel-Fishelson & Hershkovitz, 2022; Ou Yang et al., 2023), our results prove otherwise. Instead, it is the formulation of problems, solving tasks, and solutions that can be applied by everyone (Wing, 2006), and we extended it to any field, particularly CALL. The nature of VE can encompass both linguistic and non-linguistic skills, as well as other competences, as noted by O'Dowd and Ware (2009). Moreover "The Council of Europe's Common European Framework of Reference for Languages (2001), a publication that has become the key reference for syllabus and textbook design across Europe in recent years, proposes that tasks need to take into account a wide range of 'non-linguistic' aspects such as sociocultural knowledge, intercultural awareness, intercultural skills, an ability to learn and study skills" (as cited in O'Dowd & Ware 2009, p. 4). As a result, the validation and development of a new conceptual framework for CT in CALL has allowed us to incorporate CT skills that the CEFR did not identify.

Similarly, the factorial structures of ITTEF also underwent validation in VE. Thus, alongside previous technology acceptance models that have been validated in various fields of CALL disciplines, such as TAM, UTAULT, and TPB in LMOOC (Rahimi, 2023) and MALL (Zhang et al., 2023), this study added the ITTEF to the list of TAMs' models that were integrated into the CALL fields.

Table 11
The truth value table of the CTsCALL, and ITTF for the configuration to predict learners' intention.

AB	AL	EV	GE	ITF	TTF	EV	CL	number	IT	raw consist.	PRI consist.	SYM consist
1	0	0	1	1	1	1	1	2	1	1	1	1
0	1	0	1	1	0	0	0	1	1	1	1	1
1	0	0	1	0	1	0	0	1	1	1	1	1
1	1	0	1	0	1	0	0	1	1	1	1	1
0	0	0	1	0	1	1	0	1	1	1	1	1
0	1	0	1	0	1	1	0	1	1	1	1	1
1	0	0	1	1	1	1	0	1	1	1	1	1
0	1	0	1	1	1	1	0	1	1	1	1	1
0	1	0	1	1	1	1	1	2	1	0.998	0.987	0.987
1	1	0	1	1	1	0	1	1	1	0.997	0.982	0.982
1	1	0	1	1	1	1	1	15	1	0.960	0.911	0.919
1	1	0	1	1	0	1	1	1	1	0.983	0.909	0.909
1	1	0	0	1	1	1	1	1	1	0.972	0.780	0.780
1	1	0	0	1	1	1	0	2	1	0.963	0.757	0.755
1	0	0	0	1	1	1	1	1	1	0.971	0.752	0.752
1	1	0	0	0	1	1	1	1	1	0.970	0.742	0.742

Notes: AB: Abstraction; AL: Algorithmic thinking; CL: Collaboration; EV: Evaluation; GE: Generalization; ETF: Environmental-technology-fit; ITF: Individual-technology fit; ETF: Environmental-technology-fit: TTF: Task-technology-fit; ITU: Intention to use.

Table 12
Result of the fsQCA analysis.

Configurations	Solutions															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Abstraction	●			●	⊗	⊗	⊗	⊗	⊕	⊕	⊕	⊕	⊕	⊗	⊗	⊗
Evaluation	⊗	⊗	⊗	⊗	⊗	⊕	⊕	⊕	⊕	⊕	⊕	⊕	⊕	⊕		⊕
Generalization	⊗	⊗	⊗		⊗	⊕			⊕	⊕	⊕	⊗	⊕	⊕	⊗	⊕
Algorithmic Thinking	⊗	●			●		⊗	⊗	⊕	⊕	⊕		⊗	⊗	⊕	⊗
Collaboration	⊗	⊗	●	⊗		⊗	⊗	⊗	⊗	⊗	⊗					⊗
Task fit	⊗	⊗		⊗	⊗		⊗			⊕	⊕		⊕	⊗	⊗	⊗
Environmental fit			⊗	⊗	⊗	⊗		⊗		⊕		⊗		⊗	⊗	
Individual fit	⊗	⊗	⊗	⊗		⊗	⊗	⊗	⊕		⊕	⊗	⊗	⊗	⊗	⊗
Consistency	0.855	0.813	0.877	0.904	0.968	0.965	0.951	0.953	0.857	0.866	0.877	0.934	0.937	0.971	1	0.972
Raw coverage	0.215	0.215	0.351	0.227	0.216	0.412	0.552	0.557	0.314	0.315	0.320	0.205	0.331	0.374	0.237	0.367
Unique coverage	0.005	0.004	0.009	0.006	0.019	0.013	0.012	0.009	0.001	0.003	0.012	0.006	0.006	0.013	0.006	0.003
Overall consistency: 0.845																
Overall coverage: 0.814																

Note: The small black circle ⊗ represents the peripheral condition, the big black circle represents the core condition (●), The circle with the positive sign (⊕) illustrates don't care conditions, and the blank ones represents the absence of the condition.

5.2. The role of CTsCALL in shaping language learners' ITEFFT in virtual exchange

To answer the second research question, we generally found that among CTsCALL, only three components fit with task, environment, and learners' individual capabilities. In fact, in our CTsCALL, abstraction refers to skills that learners need to be very attentive to by focusing on critical information rather than details while solving VE tasks. According to the formative model, abstraction positively predicted ITF, TTF, and ETF. Consequently, it is possible to infer that as language learners were able to solve language tasks in VE by obtaining key information rather than focusing on details, VE was more useful to them as a means of exchanging language and culture while acquiring problem-solving skills. Furthermore, abstraction was associated with a higher degree of shared variance with learners' individual technology fit ($\beta = 0.301$) and exchange tasks ($\beta = 0.286$), suggesting that language tasks that require learners to solve them by abstraction did not only correspond to their individual skills but also increased them. Moreover, they perceived VE to be a suitable environment to carry out abstraction while solving language tasks. Several factors accounted for our findings, including the well-designed tasks in our VE project, which aligned with language learners' overall abilities. As a result of our VE, several tasks were performed in multiple environments, including immersive virtual reality, Kahoot, Learning Managing Systems (LMS) like Moodle, AI, and a WhatsApp group where language learners from Spain exchanged information with Cypriot and Irish students and learned about the target cultures through activities that involved abstraction skills. Moreover, the fsQCA analysis revealed that nine out of sixteen solutions contained abstraction, especially when algorithmic thinking was lacking (solutions 4 and 6), high levels of intention may be achieved with the presence of collaboration and individual task fit.

Studies have demonstrated that language tasks that require learners to find key information can increase creativity (Nguyen et al., 2020), meta-linguistic awareness, accuracy, and fluency (O'Rourke, 2007). These findings prompted them to conclude that such language and cultural tasks might contribute to learners' development of abstraction skills, thus influencing how they view VE. O'Dowd and Ware (2009) also emphasized the importance of task design for any electronic exchange. In general, these findings are consistent with Oakley et al.'s (2017), who found that such language tasks were capable of developing students'

Table 13
The sufficient configuration from sub-sample 1.

Configurations	Raw coverage	Unique coverage	Consistency
Abstraction*~Colabration*~Enviroment*~Evaluation*~Generalization*~Individual*~Task	0.236	0.001	0.803
Abstraction*~Alghorithm*~Colabration*~Enviroment*~Evaluation*~Generalization*~Task	0.242	0.003	0.792
~Alghorithm*Colabration*~Enviroment*~Evaluation*~Generalization*~Individual*~Task	0.205	0.001	0.831
~Abstraction*~Alghorithm*Colabration*~Enviroment*Generalization*~Individual*~Task	0.210	0.001	0.800
~Abstraction*Alghorithm*~Colabration*Enviroment*Evaluation*Generalization*Task	0.303	0.004	0.976
Abstraction*Colabration*Enviroment*~Evaluation*~Generalization*Individual*Task	0.283	0.003	1
Abstraction*Colabration*Enviroment*Evaluation*Generalization*Individual*Task	0.449	0.009	0.989
~Abstraction*~Alghorithm*Colabration*Enviroment*Evaluation*~Generalization*~Individual*~Task	0.213	0.013	0.945
~Abstraction*~Alghorithm*~Colabration*Enviroment*~Evaluation*Generalization*~Individual*Task	0.262	0.01	0.963
Abstraction*Alghorithm*~Colabration*~Enviroment*Evaluation*~Generalization*~Individual*Task	0.223	0.006	0.956
~Abstraction*Alghorithm*Enviroment*Evaluation*Generalization*Individual*Task	0.319	0.0008	0.989
Abstraction*Alghorithm*Colabration*Enviroment*Evaluation*Generalization*Individual	0.430	0.001	0.988
Abstraction*Alghorithm*Colabration*Enviroment*Generalization*Individual*Task	0.475	0.212	0.989
Alghorithm*Colabration*Enviroment*Evaluation*Generalization*Individual*Task	0.432	0.001	0.985
Overall coverage: 0.811 Overall consistency: 0.886			

attitudes toward VE. Nevertheless, on closer inspection, they did not cover learners' attitudinal components, which are covered by our findings through bi-phenomena perspectives.

Moreover, collaboration predicted only two of ITU's antecedents. Accordingly, the more language learners collaborated to solve VE tasks, the more they perceived the value of the VE and its characteristics in learning the target culture. This finding may be due to cooperative language learning exchange, in which language learners from a wide range of different intercultural backgrounds participate in VE (O'Dowd & Ritter, 2013), skills (Luo & Yang, 2021), competence levels (O'Dowd & Ritter, 2013), as well as the nature of the tasks that have been highlighted in previous studies as focal aspects of any VE (Sevilla-Pavón & Nicolaou, 2020). Recent studies have demonstrated the importance of cooperative language exchange to develop language learners' creativity, ICC, motivation (Nguyen et al., 2020), and 21st-century digital competence (Sevilla-Pavón & Nicolaou, 2020). This finding adds to previous findings that the cooperative language nature of VE led language learners to solve language tasks through CTsCALL, culminating in perceiving its characteristics and tasks fit within their individual skills and objects. Our configuration analysis is also supported this result since it was incorporated into eleven solutions and, in particular, three solutions (9,10,11). Therefore, it had a high level of coverage to shape participant ITU.

According to our framework, generalization refers to how language learners perceive patterns in solving specific VE tasks and transfer them to real-life situations. As illustrated in the structural phase, generalization significantly predicted ITF, TTF, and ETF. Indeed, having had a higher level of skills to find how to solve tasks and use them, language learners found VE as a significant context to learn and acquire problem-solving skills in language learning since they perceived the task and the environment to fit with their individual skills. This is consistent with the *authenticity gap*, the notion that language learners perceive digital language contexts to be more closely related to real-life language use than traditional language classes (Rahimi, 2023). This finding highlighted that not only did CALL materials, particularly VE, assist language learners in acquiring the target language culture but also in acquiring the skills that are essential for 21st-century development, including CTsCALL, as well as applying these skills to the target culture(s), thereby influencing their attitudes toward VE.

This is also analogous to the European Commission's (2020) observation that *through virtual exchange activities, teachers have the opportunity to step outside of their accustomed teaching procedures and cultivate new skills necessary for the linguistic, cross-cultural, and e-learning environments that language learners encounter in their target situation.* Previous research also suggested that language learners who participated in VE were able to speak their target language confidently (Bueno-Alastuey & Kleban, 2014; Corder & U, 2010) and that they shaped their agency to use language effectively in a real-life situation (Kohn & Hoffstaedter, 2017). The current results further added to the previous findings in the literature by demonstrating that virtual exchange has the potential to enhance problem-solving skills, specifically CTsCALL, through the implementation of language and culture tasks. This in turn results in preparing language learners to apply these problem-solving skills in a real-life context by means of activating those skills required to meet 21st-century challenges (Rahimi, 2024a,b; Israel-Fishelson & Hershkovitz, 2022).

Interestingly, generalization had the highest level of shared variance among all CTsCALL with ITF ($\beta = 0.267$), meaning that language learners perceived their capabilities after using VE to transfer language skills and culture into real-life situations. The asymmetrical part of our study revealed, however, that generalization has been attributed to six solutions and is not one of the core conditions for shaping learners' intention to use VE. Additionally, of these six solutions, the ITF is present in five among all the variables, likely explaining why it shared the highest variance with GE in the symmetrical part of the study.

5.3. The mediation roles of three antecedents

We found that the three antecedents significantly predicted language learners' ITU toward VE, specifically their individual-technology fit, which had a higher shared variance ($\beta = 0.343$) with ITU. This could be related to sociocultural aspects of VE in which language learners build rapport with each other's (Chen & Sevilla-Pavón, 2023), exchange their information and experience (Gruber et al., 2023), or types of tasks (Gruber et al., 2023), and co-construct their minds (Sevilla-Pavón & Nicolaou, 2020). Alongside the modes of VE (Liu et al., 2023), tasks (O'Dowd & Ware, 2009) and tools (Barbosa & Ferreira-Lopes, 2021), the personal factors of language learners, such as their capabilities, should also be considered as successful factors to implement it while cultivating new skills such as CTsCALL. It is also confirmed by our configuration analysis, since ITF was present in all 12 solutions, particularly in 7 and 8 which had the highest coverage. The project's design, which enabled language learners to communicate using multimodal environments like Moodle, Spatial, and WhatsApp, may also relate to this finding. As O'Dowd (2007) observed, online interaction enables learners to set up collaborative activities with appropriate partners, which could escalate learners' ICC and language skills, and we have added CTsCALL to this. Previous studies (Chen et al., 2013) found a correlation between the VE task and the environment where it occurred; however, they did not explore the continuing intentions of language learners in that regard, a gap we covered in accepting (H6).

Our mediation analysis answered the study's third research question. An indirect bootstrap analysis showed that three mediators flipped CTsCALL's influence on learners' ITU. In our direct bootstrap analysis, CL significantly influenced language learners' ITU, but TTF and ETF completely reversed this effect in our mediation analysis. Similarly, the significant direct correlations between AB-ITU (t = 3.95),CL-ITU (t = 1.29), GE-ITU (t = 4.02),were changed to insignificant ones. Because they changed significance, they acted as moderator variables rather than mediator variables. Unfortunately, the environmental-technology fit could not act as mediator in our hypothesize model, while the task, and learners' capabilities significantly acted as a mediator particularly for the generalization. As a result of generalization skills, language learners can recognize patterns within the VE and apply these patterns to real-life situations. This skill is significantly facilitated by both the learners' capabilities and the VE tasks, which are influenced by the learners' intention to use the VE in the future. This aligns with Rahimi and Sevilla-Pavón (2025), who highlight the authenticity gap in VE, where language learners' current learning needs and future ideal images are covered by VE tasks to respond to their current needs as well as future objectives beyond the VE context. However, the ETF did not act as a mediator variable, meaning that in comparison with learners' capabilities and VE tasks, the VE environment had not strongly influenced the correlation between learners' CTsCALL and their intentions to use it in the future. This finding contradicts O'Dowd's (2007) assertion that 'by applying various communication tools' to perform different functions, telecollaborative partners could work on aspects of ICC best suited to each medium (p. 148). In relation to this, it should be borne in mind that the planning of VE projects should focus on class needs, not the tool itself (Dooly, 2007, p. 218), as technology cannot provide a one-size-fits-all solution for all educational situations. Nevertheless, further analysis of the asymmetrical part of our study revealed that all of the factors—TTF, ETF, and ITF—were among the peripheral conditions, meaning that, While these factors were not essential in shaping learners' ITU towards VE, they facilitated the process.

It is possible that the role played by ITF, TTF and ETF is in reaction to O'Dowd and Ware's (2009) observation, as they noted that studies of language tasks and their outcomes have been scarce. These three mediators played a crucial role in achieving the product of determining language learners' willingness to continue their cultural exchange in the future through VE. In fact, no other outcome is more important than having students' continued intention to exchange culture and language in such an environment in the future. This outcome corroborates recent findings by CALL scholars who emphasized that the success of any CALL material hinges on the user's likelihood to utilize it in the future (Rahimi, 2023; Rahimi & Tafazoli, 2022). Also, in five of the sixteen solutions, CTsCALL skills were among the core (necessary) conditions where, presenting that without the presence of them, learners' ITU cannot be shaped. This shows that CTsCALL can affect language learners' desire to use VE even when ITTEF factors are not present. However, the presence of ITTEF factors would facilitate this process.

6. Conclusion

Validation and confirmation of the conceptual frameworks of CTsCALL and ITTEF, as well as an exploration of their roles in shaping learners' ITU bi-symmetrically. Thus, the findings might have some value in theoretical and practical terms for CALL.

6.1. Theoretical contribution

On seven points, this study offers valuable contributions to the existing literature on the humanistic field in general and language teaching, CALL, and VE in particular. Among the most significant contributions of this study are the introduction of a conceptual framework for CTsCALL, the development of a scale specifically tailored to the CALL field, and the confirmation that CT skills are not limited to STEM education, as previously assumed by STEM researchers (Israel-Fishelson & Hershkovitz, 2022). These skills can also be applied to other educational fields, such as language teaching through technology and problem-solving, particularly in areas that have already been validated in diverse disciplines, including mathematics (Zhang & Savard, 2023) and the arts (Barkela, Han, & Weber, 2024). Through this validation, our field can advance alongside other areas of research in the digital age, where most researchers have already validated CT in their own contexts, ensuring we are not left behind. By validating and integrating 21st-century digital skills, we are also making progress in the field of CALL, as it is essential for the technology-driven world we live in; as technology advances, so too should the CALL field (Colpaert, 2020; Gimeno-Sanz, 2015). Moreover, in this era of technological innovation, where technology is increasingly used to solve problems rather than to merely teach (Rahimi, 2024b), language teachers and researchers are seeking frameworks and scales for problem-solving, especially at a time when AI and chatbots are being employed to assist learners. This framework and scale offer a timely and relevant solution for our field of study. Additionally, by examining serial correlations and configurations between CTsCALL, ITTEF, and learners' intentions to use VE, we have proposed a new conceptual framework for the dynamic, complex system of SLA within the context of VE (Freeborn et al., 2022; Larsen-Freeman & Cameron, 2008; Rahmi, 2023; Rahimi & Sevilla-Pavón, 2024a).

As a second important aspect, it shifts the focus of the study from addressing the teaching of languages via CALL to addressing how to solve language tasks through CALL, CTsCALL, and VE, thus responding to STEM scholars who reported that computer programming is the predominant method used for developing students' CT skills (Israel-Fishelson & Hershkovitz, 2022). Thirdly, previous studies have primarily examined the impact of VE on learners' ICC (), motivation (Rahimi & Sevilla-Pavón, 2025), engagement (Gruber et al., 2023), language skills (Zhang, 2022), and digital competence (Sevilla-Pavón & Nicolaou, 2020). However, this study offers a unique perspective on language learners' future intentions to utilize VE, taking into account the tri-perspective dimensions previously explored in previous CALL fields such as LMOOCs (Rahimi, 2023), online language teaching (Rahimi & Tafazoli, 2022), and MALL The fourth added value of this study is that, to the best of the researchers' knowledge, it is the first study in the CALL field that has used an exploratory approach and developed a theory in VE since recent studies have extensively applied action research (Luo & Gui, 2019), case studies (Ware & O'Dowd, 2008), or comparative methodologies (Chen et al., 2013). In addition, this study is the first to apply configuration analysis to the field of CALL, and it may serve as a response to Golonka et al. (2014), who reported in their critical review of 350 CALL studies that most of the CALL studies were primarily descriptive, included a small sample size, and had poor data analysis.

Another noteworthy aspect of the study was to shift the focus to simultaneously combining asymmetric and symmetric approaches rather than integrating qualitative and quantitative methodologies to produce more results, which can be a response to the criticism raised by previous reports highlighted that the majority of VE studies use qualitative data collection and analysis, and they have relatively few participants, indicating that evidence-based designs or extensive samples would not be implemented to demonstrate the effectiveness of VE (Rienties et al., 2020). As highlighted by Rahimi and Sevilla-Pavón (2024a), symmetrical research designs, such as PLS-SEM, follow fuzzy logic by identifying the factors that should be present to achieve the desired outcome. In contrast, asymmetrical research designs, like fsQCA, employ necessary logic, combining various cases that are required for the presence of the target outcome. The combination of these two research designs allows us to identify which variables are necessary conditions (without them learners' intention to use VE would not be possible) and which are not necessary conditions (their presence is not essential for achieving the target outcome, but they can facilitate the process). We also heeded a recent recommendation calling on CALL

researchers to go beyond language skills and integrate 21st-century digital skills into the field (Rahimi, 2024a,b; Rahimi & Mosalli, 2024). Lastly, the study contributed to the development of new trends within the field, which are being recommended by pioneers in the field (Colpaert, 2020; O'Dowd, 2021).

6.2. Practical contribution

Practical implications may be evident from micro, meso, and macro perspectives. From a micro perspective, language teachers and schools would be greatly interested in knowing that students are planning to learn a language and become aware of the target culture through VE with a view to incorporating it into their curricula. Essentially, this is a shift in the view from teaching language skills or subskills or familiarizing with foreign cultures with VE to solving language tasks with it, based on CTsCALL. In this regard, educators should strike a balance between teaching language skills and incorporating 21st-century digital skills, especially CTsCALL. It is important to maintain a balance between utilizing VE to enhance ICC as well as learners' learning achievement and language learners' intention to use it in the future. They should also know how to solve language tasks through CTsCALL, both directly and indirectly, in order to shape language learners' intention to learn language with technology in the future.

At the meso level, VE administrators and designers should integrate 21st-century skills, specifically CTsCALL and its components, during the design process as follows:

- The tasks where learners should apply their deductive reasoning and abstraction, incidentally knowing how to find the response without paying attention to details.
- The tasks that require learners to solve them collaboratively.
- The tasks where language learners need to recognize the patterns of how to solve specific VE tasks and apply them to other language tasks.

By designing such tasks, language learners will be able to generalize these skills, leading them to apply them in their daily lives and influencing their attitudes towards VE. In addition to designing their tasks based on CTsCALL components, they should also consider whether they are compatible with the environment and language learners' current abilities.

It is also necessary for them to provide teacher training programs and explain how teachers can apply CTsCALL when solving language tasks in this environment. Moreover, it is essential to coach language teachers in VE based on CTsCALL; thus, in addition to conducting workshops, researchers and practitioners should also coach language teachers most effectively, explaining how to engage, exchange, and lead learners to apply CTsCALL in VE.

Stakeholders in computational thinking should also be aware that other fields, particularly CALL, have validated CT. In this regard, they should advise executive managers who design robotics programs, applications, and software to design them as broadly as possible so they can be used in all fields to cultivate CT. Furthermore, they should conduct workshops for researchers, especially those in STEM fields, emphasizing the universal applicability of CT and encouraging collaboration to expand its use in our respective fields. They should also suggest designing CT according to the learners' knowledge and abilities, the task, and the intended environment.

At the meso level we developed CTsACLL framework and its instrument, and opened up a new avenue for CALL and language teaching researchers, enabling them to validate factorial structures in other CALL subfields such as LMOOCs, MALL, flipped classrooms, and others. CALL researchers should investigate the impact of CTsCALL on language learners' performance, creativity, achievement, and other psychological factors like motivation, self-regulation, emotion, and engagement. It would be beneficial if CALL researchers proceed in this manner, incorporating CTsCALL into their research areas and examining its impact on language learners' performance, creativity, achievements, and other psychological factors such as motivation, and self-regulation. The more we apply, extend, and validate CTsCALL, the more we will demonstrate its relevance to our field. It is also significant for CALL researchers who want to explore teachers' or language learners' attitudes or behavioral intention toward target language technology to explore it from ITTEF as well since recent CALL studies heavily applied TPB, or TAM. We also advised researchers who want to have two designs at the same time, such as qualitative and quantitative ones, to adopt a bisymmetric approach to their studies. Furthermore, the result opens up new areas for CEFR. Therefore, whenever syllabuses, courses, books or language activities are designed, CTsCALL skills should be included in addition to other nonlinguistic skills, such as sociocultural awareness. The final point we would like to make is to consider the implications for all pedagogical experts, researchers, practitioners and curriculum designers as follows:

Considering the rapid advancement of technology and skills, our goal should not be merely to integrate technology into language classrooms. Rather, its process is equally important, particularly in the current century, as the shape of teaching with ICT has witnessed changes to solving problems with it (Rahimi, 2024b), particularly with the developments of AI, such as ChatGPT, and new skills, such as 21st-century digital skills or CTsCALL. In the context of VE, the product aspects are also essential, since much of the research has focused on developing language proficiency or ICC. Additionally, it is imperative to identify the most effective ways to increase learners' intention to use.

7. Limitation of the study

This study is merely a first step in understanding how CTsCALL influences language learners' ITU virtual exchange. Hence, CTsCALL and ITTEF should be applied to other EFL and ESL contexts and CALL disciplines. Researchers should also validate the CTsCALL scale and use it in their research. A replication of the study objective in another study context with a larger sample size is highly recommended. Furthermore, we used self-reported data and questionnaire items to explore learners' CTsCALL and their intentions toward VE. This approach has the common limitation of potential biases, such as social desirability or recall biases. However, the use of memory aids, such as visual timelines, diaries, or other prompts, can help participants recall events more accurately and mitigate these biases. While the random sampling method may introduce some bias, applying purposeful sampling to differentiate between active and non-active students could enhance future studies by examining which types of CTsCALL lead to higher intentions to use VE. We strongly recommend that CTsCALL be applied in future studies that integrate artificial intelligence and chatbot technology, due to its problem-solving nature. Furthermore, given the quantitative nature of our data, we suggest incorporating qualitative methods such as interviews, log files, longitudinal studies and case studies to explore the potential effects of CTsCALL on language learners' ITU. Additionally, future research should consider applying other technology acceptance models, such as TAM and UTAUT, to investigate how CTsCALL influences language learners' attitudes.

CRediT authorship contribution statement

Amir Reza Rahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Conceptualization. **Ana Sevilla-Pavón:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Disclosure statement

The authors declare no conflicts of interest/no competing interests.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethical approval

The ethical permission was obtained from the heads of departments and language institutions. Participants completed a consent form that explained the purpose and procedure of the study, as well as the voluntary nature of participation; the form explained how the data would be used and how anonymity would be maintained.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2025.100607.

Appendix

The study scale and descriptive statistics

Variable	Source	Item	Mean	Standard deviation	Excess kurtosis	Skewness
AB1		When solving tasks in VE, I looked at the big picture instead of the details.	3.315	1.160	−0.676	−0.474
AB2		It is more important to me to look at the most important aspects of solving VE tasks from a whole-point-of-view rather than focusing on details.	3.272	0.957	−0.407	−0.271
AB3		When I want to solve VE tasks, I usually try to identify the key points.	3.272	1.074	−0.673	−0.298
AL1		Whenever I had a task in VE, I knew the steps I needed to follow.	3.283	0.876	−0.222	−0.295
AL2		I usually try to find effective solutions for VE tasks.	3.217	1.051	−0.509	−0.335
AL3		I usually try to lay out the steps for solving tasks in VE.	3.207	0.939	−0.428	0.053
CL1		I like experiencing collaboration and solving tasks with others in VE.	3.457	0.826	0.030	−0.211
CL2		I enjoy working cooperatively with international students on several tasks in VE.	3.435	0.851	−0.605	−0.008
CL3		I like solving problems related to group projects together with others in VE.	3.489	0.927	−0.468	−0.218
EV1		I try to find the best solution in VE when faced with a challenging situation such as solving a task.	3.500	0.715	0.848	−0.545
EV2		I usually think of the best answer for our tasks in VE.	3.304	0.817	−0.634	−0.015
EV3		I usually think of a fast solution to solve the tasks in VE.	3.272	0.848	−0.337	−0.558
GE1		My VE experience can help me solve tasks and use language in real-life situations.	2.652	1.005	−0.673	0.096
GE2		Based on my experience in VE, I can find the easiest way to solve different language tasks.	2.826	0.962	−0.794	0.284
GE3		I can apply familiar VE solutions to solve other language tasks.	2.761	1.046	−0.839	0.092
ITF1		I could independently and cooperatively solve tasks in VE.	3.348	0.813	0.773	−0.727
ITF2		I could actively participate in various tasks in VE.	3.435	0.864	−0.165	−0.052
ITF3		I tried to interact with others to solve tasks and performed well in VE.	3.359	0.867	0.080	−0.266
TTF1	Goodhue and Thompson (1995)	The VE tasks were well designed.	3.337	0.924	−0.333	−0.223
TTF2		The VE tasks were real/realistic.	3.293	0.962	−1.128	−0.028
TTF3		I found VE tasks suitable for my learning requirements.	3.359	0.904	−0.579	−0.241
ETF1	Wu and Chen (2017)	The VE environment provided suitable conditions for solving language tasks.	3.196	0.875	−0.563	−0.001
ETF2		VE provided real-time problem-solving in the language exchange environment.	3.359	0.973	−0.737	0.011
ETF3		The conditions provided by the VE were optimal for solving tasks.	3.359	0.829	−0.213	−0.296
ITU1	Lu and Yang (2014)	Having learned language or exchanged cultural information in a VE, I will continue to use it.	3.402	0.860	0.178	−0.367
ITU2		In general, I am willing to exchange language and solve tasks in VE.	3.348	0.890	−0.429	−0.093
ITU3		It is my intention to join another VE in the near future.	3.370	0.869	−0.053	−0.499

Data availability

Data will be made available on request.

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