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Modelling sequential readiness and learner profiles for extended reality-based learning in open and distance education

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Abstract

Purpose – This paper reports on a study that was intended to examine how students' readiness shapes their perceptions of extended reality (XR)-based learning in open and distance learning (ODL) whilst also identifying latent learner profiles and exploring students' expectations regarding XR- and AI-supported learning.

Design/methodology/approach – A mixed-method sequential explanatory design was employed. Quantitative data were collected from 122 students enrolled in an Earth and Space Science course at Universitas Terbuka, Indonesia, who had prior exposure to XR-supported learning activities. The relationships amongst Technology Readiness, Cognitive Readiness, Affective Readiness and Perceptions of XR-Based Learning were analysed using partial least squares structural equation modelling whilst learner heterogeneity was examined using finite mixture partial least squares (FIMIX-PLS). Qualitative responses were analysed through thematic analysis.

Findings – The results revealed a sequential readiness mechanism: Technology Readiness significantly predicted Cognitive Readiness, Cognitive Readiness significantly predicted Affective Readiness and Affective Readiness emerged as the strongest direct predictor of Perceptions of XR-Based Learning. FIMIX-PLS identified two latent learner segments with different readiness configurations. The qualitative analysis generated three themes: the visualisation of abstract concepts and improved understanding, interactivity and learning engagement and accessibility and ease of use.

Research limitations/implications – The study was conducted in a single-course context using purposive sampling, which may limit the broader generalisation of the findings.

Practical implications – XR implementation in ODL should support not only technological access but also students' cognitive and affective preparedness.

Social implications – The findings highlight the importance of accessible and inclusive XR-supported learning in widening meaningful participation in ODL, particularly for learners who study independently and rely heavily on digital environments.

Originality/value – The study offers a sequential readiness model for XR-based learning in ODL and highlights learner heterogeneity in immersive learning contexts.

Keywords Extended reality, Open and distance learning, Technology readiness, Cognitive readiness, Affective readiness

Paper type Research article

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1. Introduction

Open and distance learning (ODL) institutions are expected not only to expand access to higher education but also to maintain the quality of learning in increasingly digital environments. As educational innovation accelerates, open universities must ensure that technology adoption enhances meaningful learning, learner engagement and pedagogical quality rather than merely introducing new technologies (Olney and Luo, 2021). Recent discussions have further emphasised the importance of placing learners at the centre of digital transformation, particularly as institutions adopt artificial intelligence (AI) and other emerging technologies (Ismail *et al.*, 2025; Lim *et al.*, 2025).

Among these innovations, extended reality (XR), including virtual reality (VR) and augmented reality (AR), has gained considerable attention for its ability to provide interactive, immersive and spatially rich learning experiences. Previous studies have demonstrated that XR can enhance conceptual understanding, engagement and learning outcomes, especially when students need to interpret abstract, dynamic or visually complex concepts (Beck, 2019; Bower and Jong, 2020; Burke *et al.*, 2025; Cao *et al.*, 2023; Di Natale *et al.*, 2020; Hamilton *et al.*, 2021; Xu *et al.*, 2022). These advantages are particularly relevant in science education where visualisation plays a crucial role in conceptual development (Hartini *et al.*, 2024; Tene *et al.*, 2024; Zhang *et al.*, 2025).

In ODL contexts, XR offers opportunities to overcome representational and engagement limitations commonly associated with remote learning (Childs *et al.*, 2023; Sadanala *et al.*, 2025). However, the effectiveness of XR depends not only on technology availability but also on learners' readiness, access to digital infrastructure and institutional support (Ronaghi *et al.*, 2024). Studies conducted in Indonesia similarly indicate that successful participation in online learning requires technological access, self-management and learner readiness (Belawati *et al.*, 2023).

Despite growing interest in XR, limited research has examined readiness for XR-based learning in ODL environments. This gap is particularly evident in Earth and Space Science (IPBA) where topics such as Earth's structure, tectonic processes, eclipses and planetary systems are abstract and spatially demanding. At Universitas Terbuka, much of the IPBA content remains text- and image-based, potentially limiting students' ability to construct accurate mental models. Consequently, understanding students' readiness for XR-supported learning has become an important area of investigation.

As illustrated in Figure 1, the conventional LMS-based learning materials used in the IPBA course mainly rely on static text and images, which provide limited support for visualising abstract and spatial scientific concepts.

To address these limitations, XR-supported learning materials were integrated into the LMS to provide more interactive and visually rich learning experiences. The XR-based materials were designed to support students in exploring scientific objects, structures and processes that are otherwise difficult to observe through conventional online resources. Figure 2 presents an example of the XR-based learning interface used in this study. This intervention was developed not merely as a technological add-on but as a pedagogical response to the challenge of teaching abstract science content in ODL environments.

The effectiveness of XR-based learning depends not only on technology but also on learners' readiness to process and engage with immersive environments. According to cognitive load theory, learning complex content requires the ability to manage and organise demanding information in working memory (Paas and Van Merrienboer, 2020; Sweller, 2020, 2024). Although previous studies have examined technology acceptance, immersion, self-efficacy, intention to use and engagement (Dwivedi *et al.*, 2019; Hmoud *et al.*, 2023; Jeyaraj *et al.*, 2023; Lin *et al.*, 2024; Xie *et al.*, 2022), limited research has conceptualised readiness as a sequential process linking Technology Readiness, Cognitive Readiness and Affective Readiness. Therefore, this study investigates these relationships and learner heterogeneity in XR-based learning using FIMIX-PLS, supported by qualitative evidence on students' expectations regarding XR and AI (Riandi *et al.*, 2026).

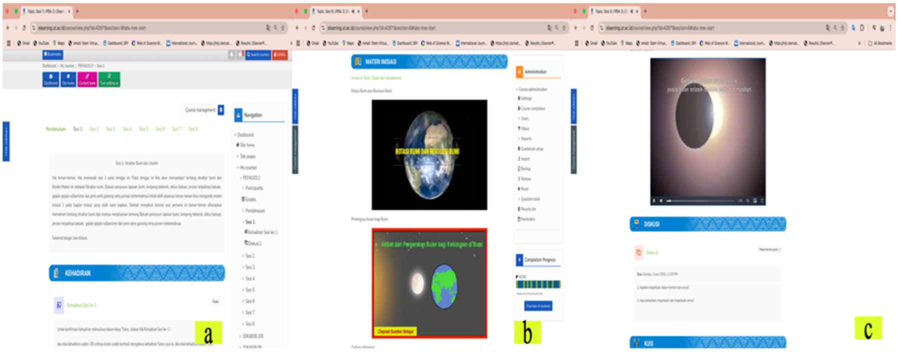

Figure 1. Example of conventional LMS-based IPBA learning material: (a) Structure of the Earth; (b) Solar rotation; (c) Solar eclipse

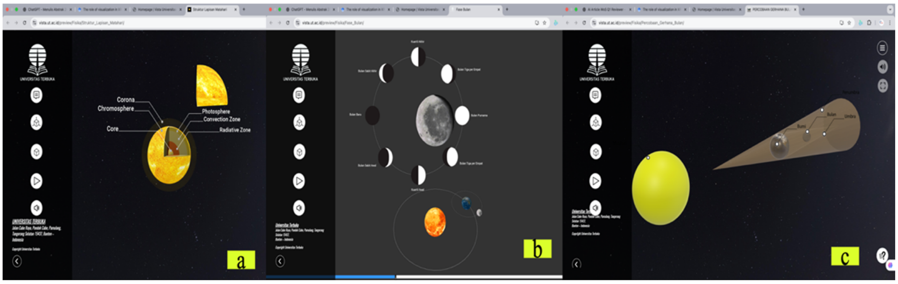

Figure 2. Example of XR-based learning material integrated into the LMS: (a) XR-based Earth structure; (b) Lunar cycle; (c) Lunar eclipse

2. Extended reality-based learning, readiness and learner diversity in open and distance education

The literature suggests that XR has significant potential to enhance learning quality in higher education and ODL, particularly for abstract, dynamic and visually demanding content. Studies have shown that VR, AR and related immersive technologies can improve conceptual understanding, learner engagement and learning experiences by providing interactive and spatially rich representations of knowledge (Beck, 2019; Bower and Jong, 2020; Burke *et al.*, 2025; Di Natale *et al.*, 2020; Hamilton *et al.*, 2021; Lin and Yu, 2023; Xu *et al.*, 2022). These benefits are especially relevant in science education where learners often need support to visualise complex processes and structures that are difficult to observe directly (Tene *et al.*, 2024; Zhang *et al.*, 2025). However, research in ODL emphasises that educational innovation depends not only on technology availability but also on effective pedagogical integration and learner support (Olney and Luo, 2021; Lim *et al.*, 2025).

Research further indicates that readiness for technology-enhanced learning is multidimensional, encompassing technological access, self-regulation, learner autonomy, digital literacy and motivation (Belawati *et al.*, 2023). In XR environments, learners must also interpret complex visual information whilst engaging in largely self-directed learning. Contextual factors such as Internet access, device availability, infrastructure and digital empowerment, therefore, play a critical role in determining the effectiveness of XR implementation (Ronaghi *et al.*, 2024).

Although previous studies have focused on technology acceptance, self-efficacy, immersion and engagement (Dwivedi *et al.*, 2019; Xie *et al.*, 2022; Jeyaraj *et al.*, 2023; Lin *et al.*, 2024), limited research has examined readiness as a sequential process involving Technology Readiness, Cognitive Readiness and Affective Readiness. Moreover, learner heterogeneity may produce distinct readiness profiles in ODL settings (Paas and Van Merriënboer, 2020; Sweller, 2020, 2024; Doo and Kim, 2024).

3. Methodology

3.1 Research design

This study employed a mixed-method sequential explanatory design. The quantitative phase was conducted first to examine the structural relationships among the main readiness constructs and students' perceptions of XR-based learning. The qualitative phase was then used to enrich and interpret the quantitative findings by exploring students' learning difficulties and expectations regarding the use of XR and AI in the IPBA course. This design was selected because the study aimed not only to test statistical relationships among readiness variables but also to understand how students described the value and challenges of XR-based learning in an ODL context.

3.2 Research context and participants

The study was conducted in the Earth and Space Science (*Ilmu Pengetahuan Bumi dan Antariksa*; IPBA) course at Universitas Terbuka, Indonesia. In this course, XR-supported materials were integrated into the learning management system (LMS) to support students' understanding of abstract, dynamic and spatially demanding scientific concepts.

The participants were 122 students who had prior experience with XR-supported learning activities in the course. Purposive sampling was used to ensure that all respondents had direct exposure to XR-based materials and were therefore able to provide informed responses regarding their readiness and perceptions. The sample size was considered adequate for the present PLS-SEM analysis because the revised structural model was relatively parsimonious and each core construct was measured using five indicators. Nevertheless, the study acknowledges that the use of purposive sampling and a course-specific sample may limit broader generalisation.

3.3 Variables and instruments

This study measured six variables: Technology Readiness (TR), Cognitive Readiness (CR), Affective Readiness (AR), Perception of XR-Based Learning (PXA), prior knowledge and learning style. The four core constructs were assessed using a five-point Likert-scale questionnaire, with higher scores indicating greater readiness or more positive perceptions. Technology Readiness reflected students' access to and confidence in using digital technologies. Cognitive Readiness represented preparedness for independent learning and for understanding complex visual-spatial content. Affective Readiness measured students' attitudes, comfort, interest and motivation toward technology-enhanced learning. Perception of XR-Based Learning captured students' perceived value of XR and AI in supporting meaningful and engaging learning experiences.

The operationalisation of these constructs was informed by the broader literature on online learning readiness and technology-enhanced learning. In particular, the multidimensional view of readiness developed by Belawati *et al.* (2023) informed the treatment of readiness as involving not only access to technology but also learner autonomy, motivation and digital capability. Likewise, the inclusion of technology-related access and usage conditions was aligned with evidence that AR adoption in higher education is shaped by Internet availability, device access and other contextual conditions that enable effective participation in immersive learning environments (Ronaghi *et al.*, 2024).

Each of the four core constructs was measured using five statement items, resulting in a total of 20 questionnaire items. To enhance methodological transparency, the full wording of the questionnaire items for TR, CR, AR and PXA should be presented in a dedicated instrument table in the main text or in the appendix. The research variables, their operational definitions, instrument types and number of items are summarised in Table 1.

Prior knowledge was evaluated using a 10-item Basic IPBA Concept Test developed to examine students' preliminary understanding of essential Earth and Space Science concepts. The instrument addressed several foundational topics, including the structure of the Earth, tectonic processes, atmospheric layers, eclipses and planetary systems. Learning style was identified through a brief learning preference inventory adapted from the VARK framework, encompassing Visual, Auditory, Reading/Writing and Kinaesthetic dimensions. However, because learning style was treated only as a supplementary variable and was not incorporated into the final explanatory model, its role in this study was limited to interpretive support rather than serving as a core analytical variable.

The complete wording of the questionnaire items for the four principal constructs is provided in Appendix A. In addition, the Basic IPBA Concept Test and the learning style inventory are presented in Appendix B and Appendix C, respectively.

3.4 Quantitative data analysis

Quantitative data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. The analysis was conducted in two stages: the assessment of the measurement model and the assessment of the structural model. The measurement model was evaluated through outer loadings, Average Variance Extracted (AVE) and composite reliability. Following common PLS-SEM criteria, which are also applied in readiness instrument development, indicators with outer loadings above 0.70 were considered acceptable whilst AVE values above 0.50 and composite reliability values above 0.70 indicated adequate convergent validity and internal consistency (Belawati *et al.*, 2023).

Based on the revised model specification, the study focused on the structural relationships among Technology Readiness, Cognitive Readiness, Affective Readiness and Perception of XR-Based Learning. The conceptual model tested in this study is presented in Figure 3.

As shown in Figure 3, the model proposes a sequential readiness mechanism in which Technology Readiness functions as a foundational condition for Cognitive Readiness, Cognitive Readiness strengthens Affective Readiness and Affective Readiness directly shapes

Table 1. Summary of research variables, operational definitions and instruments

Variable	Brief operational definition	Instrument type	Number of items
Technology readiness	Readiness in terms of digital resources, experience and confidence in using technology for learning	Five-point Likert questionnaire	5
Cognitive readiness	Readiness to understand content, learn independently and manage cognitively demanding visual-spatial material	Five-point Likert questionnaire	5
Affective readiness	Attitudes, interest, comfort, motivation and confidence toward technology-enhanced learning	Five-point Likert questionnaire	5
Perception of XR-based learning	Expectations and perceived value of XR and AI for supporting IPBA learning	Five-point Likert questionnaire	5
Prior knowledge	Initial understanding of basic IPBA concepts	Multiple-choice test	10
Learning style	Dominant learning preferences based on the VARK framework	Multiple-choice preference inventory	3

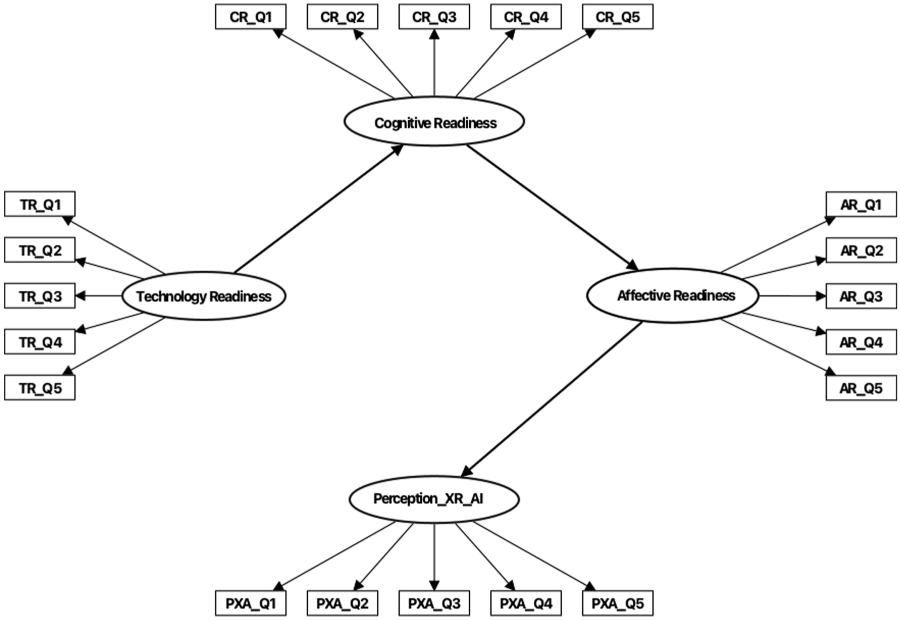

Figure 3. Revised conceptual model of learners' readiness for XR-based learning

students' Perception of XR-Based Learning. In this model, students' perceptions of XR-based learning are not assumed to emerge solely from technological familiarity but rather through an inter-related sequence of technological, cognitive and affective preparedness.

Accordingly, the following hypotheses were tested:

H1. Technology Readiness positively affects Cognitive Readiness.

H2. Cognitive Readiness positively affects Affective Readiness.

H3. Affective Readiness positively affects Perception of XR-Based Learning.

In addition, paths involving Learning Style were initially examined as supplementary relationships. However, because these paths were statistically non-significant, Learning Style was not retained in the final structural figure and was reported only as a supplementary part of the analysis. To identify potential heterogeneity in students' readiness patterns and perceptions of XR-based learning, Finite Mixture Partial Least Squares (FIMIX-PLS) was also employed. This procedure was used to detect possible latent learner groups with differing structural response patterns.

3.5 Qualitative data collection and analysis

Qualitative data were collected using two open-ended questions administered after students experienced XR-supported learning. The questions explored students' learning difficulties and their expectations regarding the use of XR and AI in the IPBA course. Responses to the first question provided contextual information on barriers to science learning whilst responses to the second question served as the primary source for examining students' expectations regarding immersive learning. The data were analysed through thematic analysis following Braun and Clarke (2006). The analysis involved repeated reading of the responses, initial coding, grouping similar codes into categories and refining them into broader themes. Because the study focused on students' perceptions and readiness for XR-based learning, the second question received primary analytical attention whereas the first was used to contextualise the findings. Theme frequency was considered only as an indicator of the relative prominence of ideas and representative quotations were used to strengthen the credibility and interpretation of the identified themes.

3.6 Integration of quantitative and qualitative findings

The quantitative and qualitative phases were integrated at the interpretation stage. The quantitative results were used to explain the structural relationships amongst the readiness variables. At the same time, the qualitative findings clarified how students described the value, challenges and expectations of XR-supported learning in the ODL context. This integration allowed the study to examine not only whether readiness variables were statistically related but also how those relationships could be interpreted from the learners' perspective.

4. Findings and discussion

4.1 Measurement model

The measurement model was first assessed to examine the adequacy of the indicators used to represent the four core constructs: Technology Readiness, Cognitive Readiness, Affective Readiness and Perception of XR-Based Learning. Overall, the retained core constructs demonstrated acceptable convergent validity and internal consistency. Most indicators showed satisfactory outer loadings on their respective constructs whilst the Average Variance Extracted (AVE) and composite reliability values met the recommended thresholds for construct adequacy. These results indicate that the retained indicators were sufficiently reliable for use in the structural model analysis.

Amongst the four core constructs, the indicators for Cognitive Readiness, Affective Readiness and Perception of XR-Based Learning showed consistently strong measurement performance. Technology Readiness showed relatively greater variation across its indicators but the construct remained acceptable at the overall level and was therefore retained in the final model. By contrast, Learning Style showed weaker measurement performance and did not demonstrate a substantive explanatory role in the structural analysis. For this reason, Learning Style was treated as a supplementary variable rather than a core component of the final explanatory model.

4.2 Structural model

The revised PLS-SEM results confirmed a significant sequential readiness mechanism in XR-based learning. Technology Readiness had a positive and significant effect on Cognitive Readiness ($\beta = 0.600$, $t = 6.636$, $p < 0.001$). Cognitive Readiness also had a positive and significant effect on Affective Readiness ($\beta = 0.678$, $t = 10.535$, $p < 0.001$). In turn, Affective Readiness had a strong positive effect on Perception of XR-Based Learning ($\beta = 0.830$, $t = 21.721$, $p < 0.001$). These findings indicate that students' perceptions of XR-based learning are formed through a progressive process in which technological preparedness supports cognitive readiness, cognitive readiness strengthens affective readiness and affective readiness directly shapes the perceived value of XR-supported learning.

Importantly, the direct path from Technology Readiness to Perception of XR-Based Learning was not retained in the final model. The results suggest that the effect of technological readiness is more appropriately explained through an indirect sequential pathway rather than as a direct determinant of perceptions of XR-based learning perception. In other words, students' familiarity with and access to technology appear to function as enabling conditions that support higher-order cognitive and affective readiness, which subsequently shape their perceptions of XR-based learning.

4.3 Supplementary relationships involving learning style

In addition to the core structural paths, supplementary paths involving Learning Style were examined. However, none of these relationships was statistically significant. Learning Style did not significantly predict Cognitive Readiness ($\beta = -0.092$, $t = 0.477$, $p = 0.633$), Affective Readiness ($\beta = 0.392$, $t = 0.998$, $p = 0.318$) or Perception of XR-Based Learning ($\beta = 0.052$, $t = 0.385$, $p = 0.700$). The path from Technology Readiness to Learning Style was also not significant ($\beta = 0.170$, $t = 1.115$, $p = 0.265$). These findings indicate that Learning Style did not make a substantive explanatory contribution to the final model and was therefore not retained as a core structural component.

4.4 Structural path coefficients

Table 2 presents the structural path coefficients of the revised PLS-SEM model.

The significant structural sequence is also illustrated in Figure 4, which presents the revised PLS-SEM structural model with only the retained significant path coefficients.

4.5 Latent segmentation with FIMIX-PLS

To explore possible heterogeneity in students' readiness patterns, FIMIX-PLS analysis was conducted. The results indicated the presence of two meaningful latent learner segments. Although both segments were situated within the same overall readiness framework, they showed different emphases in the structural pattern.

The first segment appeared to be characterised by a stronger role of cognitive and affective readiness in shaping students' perceptions of XR-based learning. For this group, positive perceptions of XR were more closely associated with their preparedness to understand and engage with the learning experience at both cognitive and emotional levels. The second segment appeared to place relatively greater emphasis on technological readiness as an enabling condition. For these learners, access to and familiarity with digital technology played a more visible role in supporting their readiness development, although affective readiness remained important for shaping final perception outcomes.

These findings suggest that students in ODL environments are not entirely homogeneous. Instead, they may display different readiness configurations that influence how XR-based learning is experienced and valued. The segmentation pattern is presented in Figure 5, which illustrates the distinction between the two latent learner groups identified through FIMIX-PLS.

4.6 Thematic analysis of students' expectations for XR-based learning

Thematic analysis identified three major themes reflecting students' expectations of XR and AI in the IPBA course: visualisation of abstract concepts, interactivity and learning engagement and accessibility and ease of use. The most prominent theme was the expectation that XR would improve understanding by making abstract, complex and spatially demanding science concepts more concrete and easier to visualise. This finding aligned with students' reports that conventional text and static images were insufficient for explaining difficult

Table 2. Structural path coefficients of the revised PLS-SEM model

Path	β	*t*-value	*p*-value	Decision
Technology readiness → Cognitive readiness	0.600	6.636	0.000	Supported
Cognitive readiness → Affective readiness	0.678	10.535	0.000	Supported
Affective readiness → Perception of XR-based Learning	0.830	21.721	0.000	Supported
Learning style → Cognitive readiness	−0.092	0.477	0.633	Not supported
Learning style → Affective readiness	0.392	0.998	0.318	Not supported
Learning style → Perception of XR-based learning	0.052	0.385	0.700	Not supported
Technology readiness → Learning style	0.170	1.115	0.265	Not supported

Figure 4. Revised PLS-SEM structural model with significant path coefficients

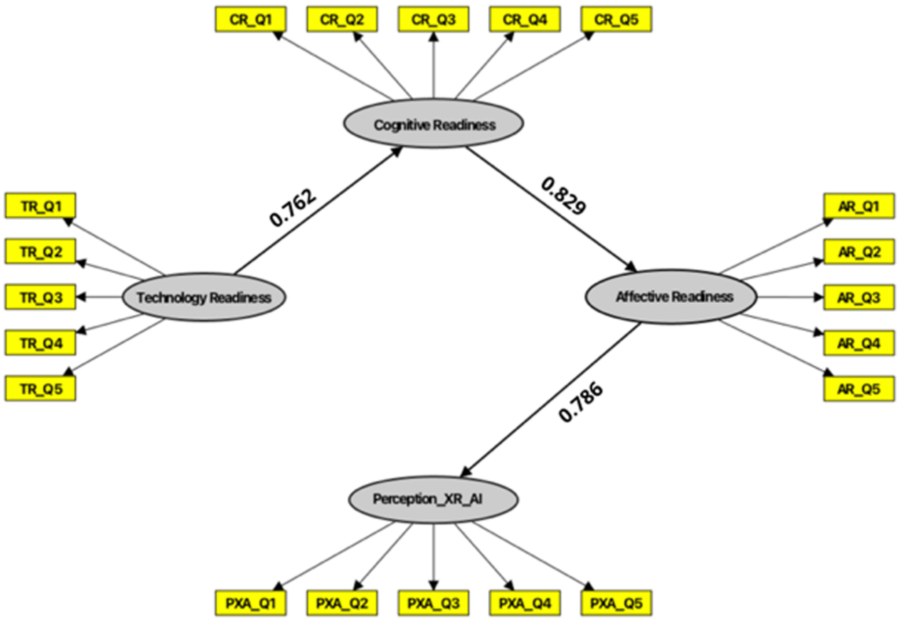

Figure 5. Latent learner segmentation based on FIMIX-PLS

scientific phenomena. Students also expected XR to create more interactive, engaging and motivating learning experiences that would encourage active participation and reduce monotony, indicating the importance of affective engagement in immersive learning. Finally, students emphasised that XR should be easily accessible, compatible with commonly used devices and practical for distance learning. These expectations highlight that the success of XR in ODL depends not only on pedagogical value but also on technological accessibility and usability.

Taken together, the qualitative results suggest that students valued XR not merely as a novel technology but as a learning support tool that should make abstract content easier to understand, increase engagement and remain accessible in everyday distance learning practice. The revised thematic structure is presented in Figure 6.

4.7 Integration of quantitative and qualitative findings

The integration of the quantitative and qualitative findings indicates that students' perceptions of XR-based learning are shaped through a sequential readiness mechanism. Quantitatively, Affective Readiness emerged as the strongest direct predictor of Perception of XR-Based Learning whilst Technology Readiness and Cognitive Readiness played foundational and intermediary roles in the readiness sequence. Qualitatively, students emphasised the importance of clear visualisation, interactive learning experiences and easy access. These expectations align closely with the quantitative pattern, suggesting that positive perceptions of XR-based learning do not arise from technological exposure alone but from the extent to which XR supports understanding, creates learning comfort and encourages meaningful engagement.

Overall, the results show that XR-based learning in ODL is most positively perceived when students are not only technologically prepared but also cognitively and affectively ready to benefit from immersive learning experiences.

4.8 Discussion

The findings demonstrate that students' perceptions of XR-based learning in ODL are shaped through a sequential readiness mechanism rather than by technological familiarity alone. Technology Readiness significantly predicted Cognitive Readiness, which subsequently strengthened Affective Readiness whilst Affective Readiness emerged as the strongest direct predictor of Perception of XR-Based Learning. These findings indicate that technological preparedness functions primarily as an enabling condition rather than a direct determinant of positive learning perceptions. Access to technology and familiarity with digital tools alone do not ensure that students perceive XR-supported learning as valuable. Instead, learners must first develop the cognitive capacity to process complex learning materials before they are able to respond positively to immersive learning experiences.

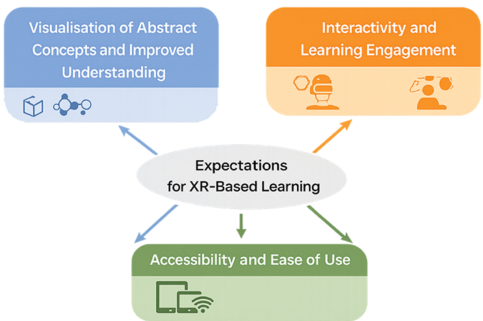

Figure 6. Revised themes of students' expectations for XR-based learning

This finding extends existing research on technology-enhanced learning, which has largely emphasised adoption-oriented constructs such as perceived usefulness, ease of use, self-efficacy and intention to use (Dwivedi *et al.*, 2019; Jeyaraj *et al.*, 2023; Leso and Cortimiglia, 2022). Although these constructs remain important for explaining technology acceptance, the present study suggests that XR implementation in ODL is better explained through a developmental readiness process. Technology Readiness establishes the foundation for learners to interact effectively with immersive technologies, Cognitive Readiness enables them to understand and manage complex learning content and Affective Readiness determines whether those experiences are ultimately perceived positively. This sequential perspective broadens previous AAOUJ findings showing that technology adoption in higher education depends on contextual factors such as device availability and Internet access (Ronaghi *et al.*, 2024). The present results indicate that these technological conditions alone are insufficient unless accompanied by learners' cognitive preparedness and affective engagement.

The mediating role of Cognitive Readiness is particularly important within science education. Previous studies have consistently highlighted the ability of XR to visualise abstract and spatially demanding scientific concepts (Beck, 2019; Tene *et al.*, 2024; Zhang *et al.*, 2025). However, immersive visualisation does not automatically improve learning outcomes. Cognitive load theory argues that meaningful learning depends on learners' capacity to organise and process complex information without exceeding the limitations of working memory (Paas and Van Merriënboer, 2020; Sweller, 2020, 2024). The present findings support this perspective by showing that students become more receptive to XR only when they possess sufficient cognitive readiness to interpret visually rich representations, construct mental models and engage in independent learning. This finding is particularly relevant for Earth and Space Science (IPBA) where many scientific phenomena are abstract, dynamic and difficult to observe directly.

Affective Readiness emerged as the strongest predictor of students' perceptions of XR-based learning, highlighting the central role of emotional and motivational factors in immersive learning environments. Students who felt confident, interested, comfortable and motivated were substantially more likely to perceive XR as meaningful and valuable. This finding is consistent with previous studies showing that learner engagement and emotional involvement are fundamental determinants of successful online learning (Doo and Kim, 2024) and that XR environments are most effective when they foster active participation and sustained motivation (Hmoud *et al.*, 2023; Lin *et al.*, 2024). It also reinforces recent AAOUJ discussions that digital transformation in open universities should prioritise learner agency, critical digital literacy and human-centred educational values rather than technological innovation alone (Lim *et al.*, 2025). Likewise, research on AI-supported learning suggests that educational technologies generate meaningful outcomes only when learners develop positive psychological responses to their use (Rafiq and Ahmad, 2026).

The qualitative findings provide additional support for the proposed readiness model. Students consistently expected XR to improve their understanding of abstract concepts, increase learning engagement and remain accessible across different technological conditions. These themes closely correspond to the quantitative findings. Improved conceptual visualisation reflects the importance of Cognitive Readiness, increased engagement reflects the contribution of Affective Readiness whilst expectations regarding accessibility reinforce the continuing importance of Technology Readiness. These findings are also consistent with previous AAOUJ research showing that successful ODL depends on technological access, learner autonomy, digital capability and self-management (Belawati *et al.*, 2023) whilst inclusive XR implementation requires adequate infrastructure and digital empowerment.

The FIMIX-PLS analysis further demonstrates that ODL learners are not homogeneous. Different learner segments exhibited different readiness configurations, suggesting that a single implementation strategy may not effectively serve all students. This finding supports the context-sensitive learning design advocated by AAOUJ (Olney and Luo, 2021) where technological orientation, conceptual scaffolding and affective support should be adjusted to learners' readiness profiles. Moreover, the non-significant contribution of Learning Style indicates that readiness-related variables explain students' responses to XR more effectively than broad preference classifications. Collectively, these findings suggest that successful XR implementation in ODL requires more than technology adoption. It requires an integrated learner-centred approach in which technological access, cognitive preparedness and affective engagement work together to create meaningful, effective and educationally valuable immersive learning experiences.

5. Conclusion

This study shows that students' perceptions of XR-based learning in open and distance education are shaped through a sequential readiness process. The findings indicate that Technology Readiness serves as a foundational condition for Cognitive Readiness, that Cognitive Readiness strengthens Affective Readiness and that Affective Readiness emerges as the strongest direct predictor of the Perception of XR-Based Learning. These results suggest that positive perceptions of immersive learning do not arise from technological familiarity alone but from the extent to which students are cognitively prepared to engage with complex content and affectively ready to experience XR as meaningful, comfortable and motivating.

The qualitative findings reinforce this conclusion. Students valued XR primarily because it was expected to help them visualise abstract concepts, increase interactivity and learning engagement and remain accessible and easy to use in distance learning contexts. Taken together, the mixed-methods findings suggest that the educational value of XR in ODL depends not only on the availability of immersive technology but also on whether the learning environment supports understanding, emotional engagement and practical usability.

The study also highlights the presence of learner heterogeneity as the FIMIX-PLS results suggest that students may differ in the readiness configurations through which they respond to XR-based learning. This implies that XR implementation in open universities should be accompanied by flexible pedagogical and technical support rather than adopting a one-size-fits-all approach.

Overall, this study contributes to the literature by proposing and empirically supporting a sequential readiness model for XR-based learning in ODL. It also extends the discussion of immersive learning beyond technology adoption by showing that cognitive and affective preparedness are central to how students perceive and value XR-supported learning. Future research may build on this model by examining longitudinal readiness development, broader learner populations and additional variables such as self-efficacy, cognitive load and a sense of presence.

Ethics statement

This study received ethical approval from the Research Ethics Committee of Universitas Terbuka, Indonesia (Approval No. B/119/UN31.LPPM/PT.00/2026). All participants voluntarily agreed to participate in the study after receiving information about the research objectives and procedures. Informed consent was obtained from all participants before data collection. Participant confidentiality and anonymity were maintained throughout the study.

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Supplementary material

The supplementary material for this article can be found online.

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