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Design and Evaluation of Interactive Radar Visualisation of Academic Performance for Parents and Students

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Abstract

This study investigates how parents and students interpret and form continued engagement intentions with a radar visualisation tool designed to present multi-subject academic performance. While data visualisation is increasingly used in education, limited empirical attention has been given to whether parents and students, who share the same performance information but hold distinct roles, respond to visualised reports through similar behaviours. To address this gap, an interactive radar visualisation was developed to present secondary school students' achievement across subjects with peer reference points. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) as an analytical framework, this study examines the determinants of continued intention to use the visualisation tool. Questionnaire data were collected from 706 parents and 264 students in a Macao secondary school. Structural equation modelling (SEM) revealed fundamentally different ideas of continued engagement. For parents, continued intention was significantly associated with performance expectancy (PE) and effort expectancy (EE), social influence (SI) and facilitating conditions (FC), suggesting the tool functioned as a decision support system for academic planning. For students, only social influence (SI) and facilitating conditions (FC) emerged as significant predictors, indicating that peer comparison and external expectations may not fit their needs. Parents also reported significantly higher continued intention than students. The finding extended UTAUT by demonstrating that core acceptance relationships are moderated by different roles, reframing technology acceptance in educational visualisation from system adoption to information interpretation. The study provides empirical evidence that visualised performance reporting functions not merely as a data display but also as a communication medium whose meaning is actively constructed by users. These insights highlight the need for role-sensitive design, emphasising actionable planning support for parents and personally meaningful, agency-oriented feedback for students, in order to foster productive home-school communication and sustained engagement with learning information.



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1. Introduction

The integration of computational data visualisation technologies in education has gained increasing attention in recent years, driven by the need for clear, accessible and actionable insights into student performance among different educational stakeholders.

However, student performance information is often difficult for non-expert stakeholders to interpret, particularly when multiple subjects and reference criteria are presented simultaneously. Advancements in programming languages such as Python, with its extensive visualisation and data processing capabilities, have played a crucial role in enabling educators to present student performance data in more interactive and intuitive ways.

Visualisation is an effective tool in presenting data in a clear and interpretable way, especially in educational contexts. Using visual approaches to present student performance offers a compact and intuitive way to represent multi-dimensional data [1]. This approach holds great promise for improving transparency and understanding of student progress, empowering students to take ownership of their learning and parents to gain insights into their child's development through showing student performance [2]. Existing research suggests that visual representations improve cognitive processing and reduce cognitive load, making it easier to identify patterns and anomalies [3,4].

With the increasing availability of educational data, there is a growing need for tools that can effectively translate multidimensional academic information into forms that support understanding, communication and decision-making. Among various visualisation formats, radar visualisation offers an intuitive way to represent performance across multiple performance measures in a single and easily interpretable figure [5], allowing stakeholders to quickly identify strengths, weaknesses and areas requiring further improvement in academic performance. While radar charts have been criticised for potential perceptual distortion and axis comparability issues, they remain well-suited to this study's context for three reasons. First, as non-experts, parents and students benefit more from a holistic overview than from precise cross-axis comparisons. Second, the radar format excels at revealing performance patterns (e.g., consistent strengths across subjects), which aligns with stakeholders' need for quick, intuitive insights. Third, interactive features (e.g., tooltips, selectable subjects) mitigate perceptual limitations by allowing users to access precise values on demand. Thus, radar visualisation was selected as an appropriate medium for facilitating educational communication.

Within educational contexts, academic performance is accessed and interpreted by both students and their parents. While students use this information for self-reflection and learning regulation, parents typically utilise it to actively monitor their child's learning progress and support academic decision-making. These two stakeholder groups rely on the same performance information but differ in responsibilities, expectations, and familiarity with academic evaluation. Consequently, the way performance information is presented may influence how each group understands and continues to engage with the information. Despite sharing the same academic records, parents and students interpret performance information for different purposes: parents for monitoring and guidance, and students for self-reflection and learning regulation. Therefore, visualisation functions as a communication medium that supports the interpretation of learning performance across educational stakeholders. However, it remains unclear whether the behavioural mechanisms underlying continued engagement with such visualisations are consistent between parents and students. To investigate this issue, an interactive radar visualisation was employed as a shared performance-reporting environment.

To explain these behavioural differences in continued engagement, this study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) model for analysis [6]. The purpose of using this model was to explain behavioural intentions toward continued use of the performance-reporting visualisation tool, and not to assess the quality of the visualisation itself. The constructs in the UTAUT model, including performance expectancy, effort expectancy, social influence, and facilitating conditions, provide a behavioural lens for analysing how different educational stakeholders form intention to continue using the

visualisation tool. Applying UTAUT to both parents and students enables comparison of whether determinants of continued use operate similarly across stakeholder roles. In addition, this study examined the moderating effects of various characteristics of different groups on the relationships between the core constructs and continued use intentions. Additionally, a Mann–Whitney U test (also known as the Wilcoxon rank-sum test) was conducted to compare the level of continued intention between the two stakeholder groups.

To examine these issues, this study investigated how parents and students respond to a radar-based performance visualisation tool for multi-subject academic performance. As two stakeholder groups engaged with academic information for fundamentally different purposes, their behavioural relationships and levels of continued engagement were expected to diverge accordingly.

Based on the stakeholder-role perspective described above, this study investigated the following research questions:

- RQ1. Do the structural relationships differ between parents and students?
- RQ2. Do parents and students differ in their continued intention to use the visualisation tool?

This study made several contributions to educational technology research. First, it moved beyond conceptualising performance visualisation as a mere reporting interface, instead framing it as a communication medium that conveys academic progress to diverse educational stakeholders. By examining both parents and students, the study demonstrated that the same performance information may be interpreted and engaged with differently depending on stakeholder roles. Second, the findings provided empirical evidence on how visualised performance reporting influences stakeholders' continued engagement with learning information. The results showed that continued intention is shaped by perceived usefulness, ease of use, and contextual and social factors, which differ between parents and students. Finally, the study employed UTAUT as an explanatory framework to interpret behavioural intention toward a performance-reporting visualisation tool. Instead of validating the theory itself, the model served to reveal behavioural differences across stakeholder groups within an educational context. This work clarifies the role of visual academic performance representations in supporting communication, monitoring, and learning awareness across home and school environments.

2. Background

This section provides an overview of the background related to this study. It outlines the general concept of effective data representation and its establishment, the applied theoretical UTAUT model, and some relevant research in this field.

2.1. Learning Dashboard in Educational Contexts

Learning dashboards have become an integral tool in educational contexts, providing a visual interface that transforms raw data into meaningful visualisations, offering a range of benefits that enhance student performance and learning experiences. It enables students and teachers to make informed decisions about learning strategies and interventions.

One of the primary benefits of learning dashboards is the ability to provide enhanced feedback and learning insights. Serrano et al. demonstrated how dashboards used in remote situations allow teachers to assist students effectively and provide personalised feedback to address specific needs [7]. Meanwhile, learning dashboards also play a crucial role in identifying learning gaps. As Pei et al. suggested, learning dashboards help educators identify and analyse performance gaps between students, which assists teachers in adjusting teaching strategies to address and improve student performance [8]. Students can learn of their own performance through learning dashboards. Hoffenson et al. noted

that learning dashboards can facilitate a personalised approach to learning by highlighting areas where specific students need improvement, allowing for a more targeted and effective way to learn [9]. Other than assisting the learning process, learning dashboards can also motivate students to engage in their coursework, fostering self-directed learning and enhancing academic outcomes. Bodily et al. found that learning dashboards were perceived positively by users as being informative and user-friendly. It is a helpful tool in learning environments to increase students' learning motivation and engagement [10].

Learning dashboards significantly contribute to improving student performance by providing feedback, identifying learning gaps, motivating students, and supporting personalised learning experiences. Through offering learning dashboards to students and teachers, it facilitates a more personalised approach to education that aligns with students' unique needs and goals, which is helpful in their learning plans and outcomes.

2.2. Effective Design for Data Representation

Visualisation is an effective way to transform raw data into comprehensible formats. It serves as a tool to support data interpretation and as a bridge connecting data analysis to informed decision-making, with the flexibility to be tailored to the unique needs of each audience. Through the use of visual aids, such as charts, graphs and infographics, complex data can be transformed into more accessible and intuitive formats, making seemingly complex ideas easier to understand. With the exponential growth of data at the present time, representing data in a digestible format is a critical way of understanding vast amounts of information, facilitating the recognition of patterns, supporting cognitive processing and enabling deeper understanding across diverse audiences.

The effectiveness of data visualisation is contingent upon appropriate design choices that align with the communication goals of the data. Different kinds of charts serve distinct purposes, and selecting the most suitable format depends on the task context and intended insights. Better choices of charts can even speed up viewers' understanding of data representation and facilitate the interpretation of data compared to plain text or tabular data. Numerous studies have shown that visual representations can uncover trends and patterns that may remain hidden in raw or tabular data [11,12] and can optimise knowledge transfer in a more intuitive and accessible way [2,12,13]. Well-designed visualisations facilitate efficient knowledge transfer and foster user engagement, highlighting the critical role in transforming data into actionable insights.

Among various types of visualisations, radar visualisation has gained attention for its ability to compare performance and analyse statistics across multiple dimensions [5]. It provides a clear interpretation of data and enables the comparison of information across different aspects. This format is particularly effective in educational contexts, where it is used to visualise student achievements across multiple criteria. By offering a comprehensive and comparative view, radar visualisation helps identify individual strengths and weaknesses, supporting personalised learning plans and stakeholder communication. The integration of such visualisations into learning dashboards and school reports allows both parents and students to access meaningful summaries of learning progress, thereby fostering greater engagement and understanding.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT) and Related Work

The Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of the most influential models in technology adoption research [6]. It plays a crucial role in determining the success or failure of a technology, which is essential for understanding how users accept and adopt the new tool [14]. The unified model, UTAUT, is mainly determined by its core factors, including PE, EE, SI and CI. It also includes moderators (gender, age,

experience, and voluntariness of use) to account for the effects between influencing factors and the intention of using a certain technology in the future. According to Venkatesh et al., it explains up to 70% of technology acceptance and usage; this level of comprehensiveness appears to be superior to previous models that describe the pathways to perceiving and promoting user acceptance [6].

In order to provide a comprehensive understanding of the core factors that are important in this research, the definition of each core factor is given below [6].

- Performance Expectancy (PE): The degree to which an individual believes that using the particular technology will help them attain gains in work performance. It includes the concepts of perceived usefulness, extrinsic motivation, job fit, relative advantage, and outcome expectations.
- Effort Expectancy (EE): The degree of ease associated with using the particular technology in one's work. It includes the concepts of perceived ease of use, complexity, and ease of use.
- Social Influence (SI): The degree to which an individual perceives that other important people (e.g., family, peers) believe they should use the particular technology. It includes the concepts of subjective norms, social factors, and image.
- Facilitating Conditions (FC): The degree to which an individual believes that there is environmental support for the use of a particular technology. It includes the concepts of perceived behavioural control, facilitating conditions, and compatibility.

The UTAUT has been extensively applied to investigate acceptance and use in education contexts, offering valuable insights into the attitudes of both students and parents. Despite the availability of various technology acceptance models and their extensions, such as the traditional TAM and models incorporating motivational factors [15], the UTAUT remains a foundational approach in most research due to its comprehensive and unified characteristics. This methodological flexibility has prompted extensive investigation into the utility of the UTAUT model within academic environments, with studies spanning diverse educational stakeholders and technological applications [15–19]. Without considering the moderators, Tan's study examined the use of an online learning website, including the core factors of the UTAUT but excluding all moderators [16]. It was found that when students believed in the benefits of using the online learning website, they were more likely to intend to put some effort into it. This result indicated that there exist some positive effects on behavioural intention. In a study that excluded the original moderating effects, Almaiah et al. extended the UTAUT by incorporating additional factors into their research model [17]. In another study, Almaiah utilised a modified version of the UTAUT to examine the factors influencing acceptance and use of an online learning system [18]. Both studies corroborated the significant influence of some factors on CI, with SI being the only exception. Li et al. considered connected classroom climate as a moderator in the UTAUT under MOOC learning; they concluded that all factors are supported by CI, and classroom climate is a significant moderator between the factors of the UTAUT and CI [19].

Beyond student-centred studies, the UTAUT model has also been extended to anticipate parental acceptance of educational technology, but this is rarely related to academic performance. According to a study by Demissie et al., they looked at the use of communication tools between schools and parents from the parents' perspective [20]. The study indicated that PE, EE and FC were significantly related to further intentions, and the age of the parents moderated the effects of some factors.

Collectively, these studies highlight the functionality and comprehensive applicability of the UTAUT in decoding the technology adoption behaviour exhibited by parents and students within educational settings. The existing literature restates the flexibility of the UTAUT model, illustrating its capability for adaptation through addition, omission or

modification according to varying theories and application contexts. The relevant modified versions of UTAUT include, but are not restricted to, those previously mentioned. The model affords considerable space for refinement, suggesting that each specific research direction might benefit from identifying a properly tailored version of the model.

3. Design

This section shows the design process for creating a radar visualisation tool. It includes information about the interviews that were conducted with users and the insights that were considered when designing and implementing the tool.

3.1. Design Considerations from Focus Group

To better design a user-centred visualisation tool for showing student academic performance that addressed real-world needs, a series of semi-structured focus groups with key stakeholders was conducted. The focus group method is well-established in exploratory research and systems design for gathering rich data on user needs and experiences [21]. The approach is particularly suitable for the design of information visualisation tools with others' perspectives, as it facilitates interactive discussion among participants, allowing them to build upon each other's ideas and reveal nuanced requirements that might not emerge from individual interviews or surveys. In the context of problem-driven visualisation research, such engagement with target users is considered a critical component of the design study methodology, particularly in the early stages of discovering domain problems and establishing the design scope [22].

A total of 20 participants were invited from Escola Choi Nong Chi Tai. To ensure a comprehensive understanding of the design requirements, a multi-perspective approach was employed to separate participants into three distinct stakeholder groups: secondary school teachers ($n = 10$), including front-line teachers and school management, students ($n = 5$) from various grade levels, and their parents ($n = 5$). This stratified sampling strategy for the focus groups was crucial for capturing the potentially diverse and sometimes conflicting needs of each user group, thereby providing a holistic view of the requirements and potential concerns. The methodological literature on focus groups suggests that segmenting participants into homogeneous groups can encourage more open discussion and allow for better detection of differences in perspectives across groups [21].

Each focus group session lasted approximately 30–60 min and was moderated by one of the authors using pre-defined interview questions. The questions were structured around four key ideas, ensuring consistency across groups while maintaining the flexibility to probe emergent topics, a strength of the semi-structured format. The development of such an interview structure is a rigorous process that contributes to the objectivity and trustworthiness of the study [23].

- How does the focus group currently understand and track student academic performance? What difficulties do they encounter?
- What kind of data or patterns would the focus group prefer to be visualised? What chart types or representations do they find most intuitive?
- What would constitute meaningful and actionable feedback for the focus group? Are there any concerns about data representation, such as privacy, ranking, or the potential for misunderstanding?
- What other suggestions does the focus group want to mention?

With informed consent from all participants (and/or students' parents), all details discussed in these focus groups were recorded, and some non-verbal cues were also captured. All discussed contents and non-verbal cues were collected, and we also repeatedly referenced some useful actual information provided by the participants that can explore their

expectations towards using visualisations. Finally, these defined themes were translated into actionable, user-centred design requirements, which served as the direct foundation for subsequent design and development of the visualisation tool.

The focus group discussions were audio-recorded, transcribed, and analysed using thematic analysis [24]. Two researchers independently coded the transcripts to ensure reliability, and themes were iteratively refined through discussion. This systematic process ensured that the resulting design requirements were grounded in stakeholder perspectives.

3.2. Design Considerations

To ensure the visualisation tool meets the needs of all stakeholders, key design decisions were guided by direct feedback from focus groups. Table 1 summarises how each group's core concerns and preferences were translated into specific features, balancing functionality with user ideas.

Table 1. Designed features aligned with focus group feedback.

Users	User Expectations	Designed Features
Teachers	- Consistency and compliance with school and legal requirements - Ease of implementation	- Act as a supplementary tool - Automated generation - Self-serve interactive implementation
Students	- Simple and intuitive design - Clearly showing strength and weakness breakdown - Avoid excessive detail or rankings	- Radar visualisation showing multi-subject performance - Highlighting imbalances without competition - Including peer average marks for reference
Parents	- Clear performance indicators - Subject-wise comparisons - Avoid information overload	- Key indicator summaries - Comparison to nearest peers but not displaying exact ranks

Based on stakeholder feedback, several design features were implemented. To address parents' need to compare multiple subjects simultaneously, all subjects were displayed on a single radar plot. To provide normative context while minimising psychological pressure, peer references were presented through shaded areas instead of as individual scores. In response to students' anxiety about peer comparison, an optional toggle was added to hide peer references. To help students interpret abstract scores, interactive tooltips displaying exact values were included. Finally, to support progress tracking, which was desired by all groups, a side-by-side comparison of current and previous term performance was incorporated. These design decisions ensured the visualisation addressed the functional and psychological needs of all stakeholders.

Visual design choices were guided by the principles of clarity, accessibility and consistency. The radar chart was selected to facilitate simultaneous comparison of different subjects, while a traditional table format was retained to present overall marks. Figure 1 presents the radar visualisation tool designed to satisfy the needs of educational stakeholders. The visualisation was embedded in the student information system, which students and parents can log in to with their user accounts to access. The visualisation tool displayed individual students' marks for every subject and a comparison of their marks with those of students in other percentiles. A clear visual hierarchy was established using colour. Hovered elements became vivid and sharply defined, while the non-interactive areas receded from attention by becoming slightly desaturated and dimmed; also, hovered elements

showed a temporary explanation presenting relevant information. The clear differentiation in visual weight directed user attention and enhances accessibility, helping individuals with low vision distinguish interactive elements from static ones more easily. On the other hand, the dual-format presentation with visual and tabular information accounted for both parents’ and students’ preferences and needs; however, its interface remained easy to understand to reduce cognitive overload. By grounding design decisions on feedback from teachers, students and parents and prioritising usability, the final design of the visualisation ensured both practical feasibility and academic value when showing student performance.

Student Analysis: XXX
Name: XXX
Student ID: s00X
Class/Academic Year: 20XX/20XX S1X (X)

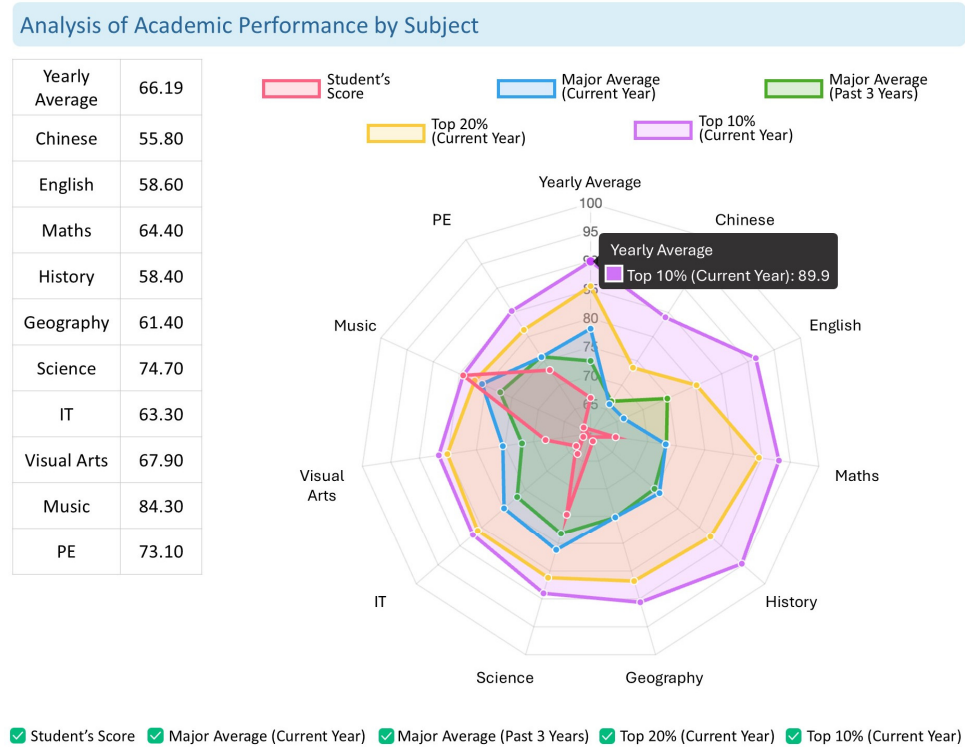


Figure 1. Interactive radar visualisation tool interface (translated from Chinese).

3.3. Technical Implementation

The radar visualisation tool was designed to transform traditional tabular performance data into an easily interpretable visualisation tool. The core of this tool is a multi-dimensional data architecture conceptualised as a data cube. The input data are typically exported from an academic transcript provided by the school system and structured into spreadsheet format. Before visualising student performance, the marks of each student are structured into a multi-dimensional array with various levels of granularity, with a methodology introduced by Golfarelli and Rizzi [25]. This structure allows for flexible analysis across several axes, including time, student categories and subjects.

After processing and structuring data, the radar visualisation is applied to offer an intuitive representation of student performance while enabling some relevant information next to the chart. The visualisation tool is generated with the Python programming language using the matplotlib, seaborn and plotly libraries, simultaneously plotting several sets of marks which can be easily tailored to an individual’s needs. Users can select the checkboxes and move their cursor over the information to personalise the content. The

design of this tool provides a clear description of students' relative standing without resorting to comparative rankings. Our design also incorporates customisation options such as colour coding, axis scaling, and legend labelling to enhance clarity. The generation of these visuals is fully automated via a computer programme that performs batch processing for entire classes or grades regularly. This automated implementation streamlines the generation of individual visualisations.

4. Methods

This section presents the design of this study. It includes an overview of the survey design and data collection, the tools and statistical approaches used for analysis, the design and consideration of moderators, and the hypotheses raised in this study.

4.1. Research Paradigm, Approach and Design

This study is positioned within a post-positivist research paradigm. Unlike pure positivism, which assumes an objective reality that can be measured with certainty, post-positivism recognises that observations are fallible and that human knowledge is shaped by context and theoretical lenses [26]. This paradigmatic stance is particularly appropriate for the present study for two reasons. First, while this research investigates the continued intention to use a radar visualisation tool, a phenomenon that can be operationalised and measured, it simultaneously acknowledges that parents and students, as distinct stakeholder groups, may interpret the same visualised performance information through different cognitive and motivational frames. As articulated in the research aims, the study seeks not only to identify predictive relationships but also to understand how these relationships differ by role, a goal that aligns with the post-positivist acceptance of multiple perspectives on a shared phenomenon [27].

Consistent with this paradigm, a quantitative research approach was adopted. Quantitative methods are well-suited for examining relationships between variables, testing theoretically derived hypotheses, and identifying patterns across groups [28]. This study draws upon the UTAUT as its theoretical foundation, which specifies a set of core constructs (PE, EE, SI and FC) and moderators that are hypothesised to influence continued intention. A quantitative approach enables the empirical testing of these hypothesised relationships and allows for statistical comparison between the parent and student subsamples—a central aim of this investigation.

This study employs a cross-sectional survey design. Survey research is widely used in technology acceptance research to collect standardised data from large samples, facilitating statistical generalisation and theory testing [29]. Given that the radar visualisation tool had been implemented in a real-world secondary school context, a survey design allowed for the efficient collection of data from both parents ($n = 706$) and students ($n = 264$) regarding their perceptions and continued intentions. The design is theory-driven. All survey items were adapted from validated UTAUT instruments and tailored to the educational visualisation context. To analyse the data, SEM was employed, which is a robust multivariate technique that enables the simultaneous examination of relationships among multiple independent and dependent constructs [30]. It is particularly appropriate for this study, as it allows for the testing of the overall UTAUT model's fit and the examination of moderating effects across the two stakeholder groups.

By integrating a post-positivist paradigm, a quantitative approach, and a cross-sectional survey design analysed through SEM, this methodology provides a rigorous foundation for investigating role-differentiated technology acceptance in educational visualisation. The following subsections detail the data collection procedures, instruments, and analytical techniques.

4.2. Data Collection and Survey Design

A purposive sampling strategy was adopted to select both the participating school and the respondents. Purposive sampling involves the deliberate selection of participants based on their ability to provide information-rich cases relevant to the research objectives [31]. The participating secondary school in Macao was selected because it cooperated with the authors in educational research to implement a radar visualisation tool for presenting student academic performance across multiple subjects, with peer reference points included. This made it an information-rich setting for investigating continued intention to use educational visualisations.

Within the school, all parents and students who had access to the radar visualisation tool during a certain academic year were invited to participate. This ensured that all respondents possessed direct experience with the technology, enabling them to provide meaningful responses regarding their perceptions and continued engagement intentions. Data were collected at two time points. The parent survey was conducted in April 2023, and the student survey in December 2023. Participation was voluntary and anonymous, and consent forms were distributed to ensure that both students and parents understood the purpose of the study and agreed to participate.

While purposive sampling does not aim for statistical representativeness in the probabilistic sense, it is appropriate for studies focused on theory testing within specific contexts [32]. The primary aim of this research is to examine whether the UTAUT model's theoretical relationships hold across two distinct stakeholder groups (parents and students) in an educational visualisation setting, rather than to estimate population parameters. The purposive selection of a school where the tool had been implemented enhances the theoretical validity of the findings by ensuring that all respondents have direct experience with the technology [33]. Two structured surveys were used in this research. The parent survey consisted of 29 items, while the student survey consisted of 36 items. The complete questionnaires are presented in Appendices A and B, respectively. Both surveys were designed based on the UTAUT model, incorporating its original core factors and modifying certain feasible moderators that affect the CI of the two participant groups in adopting this technology. The survey included questions on background information, four core factors, continued intention to use the particular technology, and an open-ended question for suggestions. Except for the background information section and the open-ended question, the questions required a response on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The survey was self-administered, voluntary and anonymous with a paper-based format for parents and a computer-based format for students. The questionnaires were distributed by the secondary school to invite all students and their parents to participate in the study. Consent forms were also provided to students and parents, indicating that students should understand the purpose of completing the questionnaires and discuss their participation with their parents before agreeing to participate. All collected data were stored in a secure location accessible only to the authors. A total of 706 validated responses were received from parents and 264 from students. All valid responses were retained for analysis. Although there were noticeable differences between the two participant groups, the sampling procedure remained consistent across both groups. The validated responses constituted the final dataset for analysis.

4.3. Data Analysis

The visualisation tool was released to parents and students for actual use, and statistical analysis was conducted to examine the moderating effects of various characteristics of different groups on the relationships between the core constructs and continued use

intentions. The analysis was performed to ensure a comprehensive understanding of parents' and students' responses regarding the effectiveness of the radar visualisation tool. The statistical software IBM SPSS Statistics 26.0 and AMOS 26.0 were the primary tools utilised to manage statistical operations in this study. Reliability analysis was conducted to assess the internal consistency of the survey instruments, while validity was evaluated to examine the extent to which the items accurately represented the theoretical constructs under investigation. Beyond basic statistical analysis, the keystone of this research was to use structural equation modelling (SEM) to analyse the collected data in order to further validate the research model. SEM is a statistical technique used to evaluate the quality of a model based on theory and previous experiences [34,35]. It is a popular method for analysing the UTAUT model and is employed to confirm whether a theory or hypothesis is fitting or adoptable. SEM is a multivariate quantitative method [36] that provides a more detailed examination of the underlying relationships between core factors and CI, providing empirical support for the proposed hypotheses. Path analysis, a specific application of SEM, was also used in this study. It decomposes the total correlation between two variables into direct and indirect effects [37] and examines how the moderators influenced the correlation between two variables. This approach provided insights into how different factors interacted and influenced continued intention to use radar visualisation.

The data collected from both parents and students were analysed using SEM with path analysis, yielding two sets of results. For inferential analysis, the Mann–Whitney U test was used to determine whether there were significant differences in responses between the two groups. This test is a non-parametric tool for comparing independent groups with ordinal data [38] and was employed to assess variations in perceptions of the radar visualisation tool across participant groups, thereby providing a deeper understanding of differences in its usage and perceived effectiveness. Following these analyses, the results were used to compare continued intention and technology usage between parents and students.

4.4. Moderator Design

This study used a quantitative research approach to evaluate the acceptance and use of a radar visualisation tool for student performance among both parents and students, aiming to determine its efficacy in enhancing their understanding of their academic progress. This research was designed based on the UTAUT model, which identified four core factors and four moderators: gender, age, experience, and voluntariness of use.

The present study adopted the four core factors of the UTAUT model while adopting the moderators to suit the educational context, a decision informed by both theoretical and contextual considerations. The surveys designed for parents and students incorporated two common moderators from the original UTAUT model, including gender and experience. Both instruments excluded the moderator for voluntariness of use, as the radar visualisation tool was mandatorily provided to all participants. To better align with the study objectives and specific characteristics of each group, several context-specific moderators were added to extend the original model.

For the parent group, four relevant moderators were included in the survey. Parents' age was considered because different age levels may hold varying perspectives on interpreting academic performance. Educational level (EdLevel) was also included, as prior research indicates that the propensity to adopt new technologies often varies with educational attainment [39]. The child's year of study was a further moderator, given that parental attention often intensifies for younger children and those nearing graduation. Finally, the frequency of parent–child discussions on academics (Freq) was included since parental involvement is a known factor influencing children's academic outcomes [40,41].

The frequency of discussions is likely to affect parents' willingness to use new tools for tracking progress.

Meanwhile, in the student group, three additional moderators were incorporated. Students' year of study was included, as academic progression influences goal-seeing behaviour; this is particularly relevant for those preparing for graduation, who must formulate appropriate learning plans based on prior performance to support their future readiness [42]. Students' educational attainment goals (Goals) were also incorporated, given that goals serve as a key motivational driver shaping learning approaches and persistence [43]. Prior research has demonstrated that different types of achievement goals are often interrelated [44]. Consistent with the parent model, the frequency of parent–child discussions on academics (Freq) was included, owing to its established importance in the student academic context.

In summary, the original UTAUT moderators were adopted as follows: gender and experience were retained for both groups; age was retained only for parents (as student age variation was minimal); voluntariness was excluded (as use of the tool was mandatory), and four context-specific moderators were added based on the educational literature (child's year of study, the frequency of parent–child discussions on academics, parents' education level, students' educational goals). These theoretically grounded additions provided a more nuanced basis for understanding the factors influencing each group's acceptance of the radar visualisation tool.

4.5. Hypothesis Design

By considering the UTAUT model, additional moderators that fit the actual research scenario, and a comparison between parents' and students' perspectives, 11 hypotheses were formulated as follows.

- **H1.** Gender significantly moderates the structural relationships in the research model.
- **H2.** Usage experience significantly moderates the structural relationships in the research model.
- **H3.** Students' year of study significantly moderates the structural relationships in the research model.
- **H4.** The frequency of parent–child discussions on academics significantly moderates the structural relationships in the research model.
- **H5.** Age significantly moderates the structural relationships in the research.
- **H6.** Parents' educational level significantly moderates the structural relationships in the research model.
- **H7.** Students' educational attainment goals significantly moderate the structural relationships in the research model.
- **H8.** Performance expectancy significantly affects continued intention to use the visualisation tool.
- **H9.** Effort expectancy significantly affects continued intention to use the visualisation tool.
- **H10.** Social influence significantly affects continued intention to use the visualisation tool.
- **H11.** Facilitating conditions significantly affect continued intention to use the visualisation tool.

5. Results

The SEM analysis was conducted separately for parents and students to examine the relationships between PE, EE, SI and FC on the CI of using the designed radar visualisation tool. Moderating variables were also analysed to assess their influence on these relation-

ships. Some moderators were drawn from the original model, while others were developed to reflect the specific contexts of the current educational system and society.

Purposive sampling was used in this research to ensure appropriate participants for this study. The survey was conducted at a local secondary school in Macao, and all parents and students were invited to complete the survey voluntarily and anonymously. A total of 706 validated parent responses and 264 validated student responses were collected. As participation was entirely voluntary and no mandatory sampling frame was applied, a traditional response rate could not be calculated. This approach was appropriate given that the purpose of the study was exploratory, which prioritises examining behavioural relationships over estimating population parameters.

Regarding sample characteristics, the parent sample was 30.03% male, 69.97% female; 79.18% aged ≤ 50 , and 20.82% aged > 50 ; 85.69% had an educational attainment of secondary school or below and 14.31% held an undergraduate or higher degree. The student sample was 48.48% male and 51.52% female, 39.77% in F1–F3, and 60.23% in F4–F6. While the sample represented a single school in Macao, it included a diverse cross-section of the school population across grade levels and demographic backgrounds. All validated responses were retained for analysis, and the results are presented in the following sections.

5.1. Preliminary Analysis

5.1.1. Descriptive Statistics

Tables 2 and 3 present the descriptive statistics for all constructs across both parent and student data, respectively. All constructs were measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 2. Descriptive statistics for parent group ($n = 706$).

	<i>M</i>	<i>SD</i>	Skewness	Kurtosis
PE	3.964	0.533	−0.126	0.748
EE	3.864	0.578	−0.199	0.580
SI	3.839	0.551	−0.241	1.237
FC	3.835	0.555	−0.361	1.834
CI	3.877	0.598	−0.468	1.541

M refers to mean; *SD* refers to standard deviation.

Table 3. Descriptive statistics for student group ($n = 264$).

	<i>M</i>	<i>SD</i>	Skewness	Kurtosis
PE	0.770	0.598	−0.709	3.038
EE	3.805	0.746	−0.512	1.271
SI	3.695	0.731	−0.497	1.736
FC	3.815	0.674	−0.334	1.077
CI	3.765	0.796	−0.330	0.211

M refers to mean; *SD* refers to standard deviation.

For the parent group ($n = 706$), mean scores ranged from 3.835 (FC) to 3.964 (PE), indicating generally positive perceptions for the visualisation tool. Standard deviations ranged from 0.533 to 0.598, suggesting relatively low variability in parents' responses. All skewness and kurtosis values were within the acceptable ranges of ± 2 and ± 7 , respectively, indicating univariate normality. For the student group ($n = 264$), mean scores ranged from 3.695 (SI) to 3.815 (FC), with standard deviations ranging from 0.598 to 0.796. Students showed higher variability in their responses compared to parents, particularly for CI ($SD = 0.796$ vs. 0.598). All skewness values were within the acceptable range (−0.709 to

−0.330). Regarding kurtosis, while PE showed a relatively higher value (3.038) in the student sample, it remained below the recommended threshold of 7.

These results suggest that the data from both samples approximated a normal distribution sufficiently for subsequent parametric analyses, supporting the use of maximum likelihood estimation in the structural equation model.

5.1.2. Correlation Analysis

Prior to testing the structural model, the Pearson correlations were examined among the five constructs for both parents and students. Table 4 presents the correlation matrices for parents (above the diagonal) and students (below the diagonal).

Table 4. Correlations of students.

	PE	EE	SI	FC	CI
PE	-	0.735 **	0.820 **	0.729 **	0.735 **
EE	0.781 **	-	0.714 **	0.810 **	0.702 **
SI	0.776 **	0.725 **	-	0.783 **	0.763 **
FC	0.779 **	0.808 **	0.777 **	-	0.807 **
CI	0.676 **	0.687 **	0.636 **	0.806 **	-

** Correlation is significant at the 0.01 level, $p < 0.01$ (2-tailed). - the correlation of a construct with itself.

All correlations were positive and statistically significant at the $p < 0.01$ level. For the parent group, CI was most strongly correlated with FC ($r = 0.807$, $p < 0.01$) and SI ($r = 0.763$, $p < 0.01$). PE showed strong correlations with all constructs, particularly with SI ($r = 0.820$, $p < 0.01$) and EE ($r = 0.735$, $p < 0.01$). Meanwhile, for the student group, all correlations were also positive and significant at the $p < 0.01$ level. Consistent with the parent group, CI was the most strongly correlated with FC ($r = 0.806$, $p < 0.01$). Notably, the relationships among all constructs in the student group appeared slightly stronger, with most correlations exceeding 0.70.

All correlation coefficients were below the threshold 0.85, indicating no multicollinearity concerns. This supported the appropriateness of including all constructs in the subsequent structural model.

5.2. Measurement Model

5.2.1. Reliability Analysis

All constructs in this study were adopted from the well-validated UTAUT model. These scales have been widely used in educational technology adoption research and have consistently demonstrated strong content validity in prior studies. Reliability was assessed by examining the internal consistency of each construct using Cronbach's Alpha. It refers to the consistency and stability of the measurement instrument, indicating how well a survey produces the same results under consistent conditions [45]. Table 5 presents the reliability analysis results. Cronbach's Alpha values of 0.70 or higher are generally considered acceptable for established scales. All Cronbach's Alpha values in this study exceeded the recommended threshold for both the parent and student groups. Parents' responses generally showed higher reliability compared to students, suggesting more homogeneous perceptions among parents. Overall, the measurement instrument demonstrated satisfactory to excellent internal consistency across both groups.

Table 5. Cronbach's alphas of core factors.

Factors	Groups	Number of Items	Cronbach's Alpha
PE	Parents	7	0.933
	Students	15	0.917
EE	Parents	4	0.926
	Students	4	0.904
SI	Parents	4	0.933
	Students	4	0.870
FC	Parents	5	0.960
	Students	5	0.852
CI	Parents	2	0.943
	Students	2	0.776

5.2.2. Convergent Validity

Convergent validity refers to the degree to which multiple items measuring the same construct are in agreement. Convergent validity was evaluated by three criteria, including that all factor loadings should exceed 0.50, composite reliability (CR) should exceed 0.70, and average variance extracted (AVE) should exceed 0.50. Tables 6 and 7 present the factor loadings, CR and AVE for all constructs in both the parent and student groups.

Table 6. Convergent validity results for parents ($n = 706$).

Construct	Item	Factor Loading ¹	CR ²	AVE ³
PE	Q7	0.856	0.939	0.688
	Q8	0.859		
	Q9	0.822		
	Q10	0.801		
	Q11	0.821		
	Q12	0.809		
	Q13	0.836		
EE	Q14	0.818	0.923	0.751
	Q15	0.876		
	Q16	0.900		
	Q17	0.868		
SI	Q18	0.820	0.905	0.704
	Q19	0.864		
	Q20	0.842		
	Q21	0.827		
FC	Q22	0.844	0.918	0.691
	Q23	0.794		
	Q24	0.845		
	Q25	0.810		
	Q26	0.859		
CI	Q27	0.920	0.917	0.847
	Q28	0.920		

Note: CR refers to composite reliability; AVE refers to average variance extracted. ¹ All loading were significant at $p < 0.001$. ² All CR values exceeded the recommended threshold of 0.70. ³ All AVE values exceeded 0.50, demonstrating good convergent validity.

Table 7. Convergent validity results for students ($n = 264$).

Construct	Item	Factor Loading ¹	CR ²	AVE ³
PE	Q6	0.716	0.939	0.516
	Q7	0.826		
	Q8	0.725		
	Q9	0.782		
	Q10	0.822		
	Q11	0.793		
	Q12	0.748		
	Q13	0.147		
	Q14	0.099		
	Q15	0.818		
	Q16	0.826		
	Q17	0.832		
	Q18	0.762		
EE	Q19	0.755	0.934	0.779
	Q20	0.794		
	Q21	0.848		
	Q22	0.879		
SI	Q23	0.918	0.911	0.720
	Q24	0.885		
	Q25	0.854		
	Q26	0.859		
FC	Q27	0.853	0.896	0.634
	Q28	0.828		
	Q29	0.767		
	Q30	0.734		
	Q31	0.880		
CI	Q32	0.782	0.901	0.819
	Q33	0.810		
	Q34	0.905		
	Q35	0.905		

Note: CR refers to composite reliability; AVE refers to average variance extracted. ¹ All factor loading exceeded the recommended threshold of 0.50. ² All CR values exceeded the recommended threshold of 0.70. ³ All AVE values exceeded 0.50, demonstrating good convergent validity.

For the parent group, all factor loadings, CR and AVE exceeded the recommended threshold, demonstrating strong convergent validity. For the student group, most factor loadings exceeded the recommended threshold. However, two items in PE (Q13 and Q14) exhibited low factor loadings. Despite these low loadings, CR and AVE values for all constructs exceeded the threshold, indicating adequate convergent validity at the construct level [30]. These two items were retained for two reasons. First, they capture essential facets of performance expectancy as defined within the UTAUT framework; deleting them would narrow the theoretical scope and compromise content validity [46]. Second, within the student sample, the construct's overall reliability and validity remained robust despite the slightly lower individual loadings. Given these theoretical and empirical considerations, the measurement model is considered adequate for testing the proposed relationships.

5.2.3. Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of the AVE for each construct exceed its highest correlation with any other construct. Tables 8 and 9 present the results for parents and students, respectively.

Table 8. Fornell–Larcker criterion (parent group, $n = 706$).

	PE	EE	SI	FC	CI
PE	(0.829)				
EE	0.735	(0.867)			
SI	0.820	0.714	(0.839)		
FC	0.729	0.810	0.783	(0.831)	
CI	0.735	0.702	0.763	0.807	(0.920)

Note: Diagonal values (shown in parentheses) represent the square root of the AVE, and off-diagonal values represent inter-construct correlations.

Table 9. Fornell–Larcker criterion (student group, $n = 264$).

	PE	EE	SI	FC	CI
PE	(0.718)				
EE	0.781	(0.883)			
SI	0.776	0.725	(0.849)		
FC	0.779	0.808	0.777	(0.796)	
CI	0.767	0.687	0.636	0.806	(0.905)

Note: Diagonal values (shown in parentheses) represent the square root of the AVE, and off-diagonal values represent inter-construct correlations.

For the parent group (Table 8), the square root of the AVE for each construct exceeded all corresponding inter-construct correlations in the parent group, confirming adequate discriminant validity. For the student group (Table 9), most constructs satisfied the Fornell–Larcker criterion. However, the correlation between FC and EE was 0.808, which slightly exceeded the square root of the AVE for FC (0.796). This suggests that students may perceive these two constructs as conceptually similar.

This slight overlap can be explained by the nature of the student learning context. For secondary school students, perceptions of ease of use (EE) and the availability of support and resources (FC) are often closely intertwined—both contribute to the overall accessibility of the tool within their learning environment. When a tool is well-integrated into classroom routines and adequately supported by teachers, students may not clearly distinguish between “this tool is easy to use” and “I have the support I need to use this tool” [47]. This conceptual overlap is particularly plausible in school settings, where technology use is mediated by institutional structures. Given that the exceedance was marginal, all other discriminant validity criteria were satisfied, and the theoretical rationale supports a close relationship between these constructs for adolescent respondents, the overall measurement model was considered acceptable for testing the proposed relationships.

5.3. Group Differences in Construct Perceptions (Mann–Whitney U Test)

A Mann–Whitney U test was conducted to examine differences in perceptions between parents ($n = 706$) and students ($n = 264$) across the five constructs, including PE, EE, SI, FC and CI. This non-parametric test was appropriate given the ordinal nature of the Likert-scale data and the unequal sample sizes between the two groups.

The results indicated that parents reported significantly higher PE than students ($U = 112,864.5$, $Z = -5.11$, $p < 0.001$, $r = 0.16$). Similarly, parents showed significantly higher SI ($U = 105,729.5$, $Z = -3.32$, $p < 0.001$, $r = 0.11$) and CI ($U = 101,379.5$, $Z = 2.26$, $p = 0.024$, $r = 0.07$). In contrast, no significant differences were found in EE ($U = 97,564$, $Z = 1.16$, $p = 0.246$, $r = 0.04$) or FC ($U = 96,060$, $Z = -0.76$, $p = 0.450$, $r = 0.02$).

Overall, these findings suggested a clear perception gap between parents and students. Parents held stronger beliefs regarding the usefulness and continued use of the radar visualisation tool, while both groups shared similar perceptions of the tool’s usability and

the availability of supporting resources. The small effect sizes indicated that although the differences are statistically significant, the practical magnitude of these differences was modest.

5.4. Structural Model Results

5.4.1. Model Fit Assessment

Table 10 presents the model fit indices for both groups, allowing readers to assess overall model quality before examining specific path relationships. Model fit was assessed for the structural model. The results indicated acceptable fit for both the parent and student groups. Four model fit indices were included in this study. In addition to traditional model fit indices, SRMR was performed, as it was shown that more accurate confidence intervals and a better test of close fit were obtained than the RMSEA. For the parent group, all goodness-of-fit indices met commonly accepted thresholds for the SEM; for the student group, SRMR fell within the acceptable range for complex behavioural models, while CFI, TLI and RMSEA indicated marginal yet adequate fit to support further structural analysis.

Table 10. Model fit indices.

Indices	Accepted Standard	Results from Parent Group	Results from Student Group
CFI	>0.9	0.929	0.861
TLI	>0.9	0.918	0.847
RMSEA	<0.08	0.079	0.091
SRMR	<0.08	0.038	0.055

5.4.2. Structural Path Analysis

After confirming acceptable model fit, the structural paths were examined. Tables 11 and 12 present the detailed path coefficients for parents and students, respectively. Following the confirmation of acceptable model fit, the structural paths were examined. The SEM model was estimated separately for parents and students to examine the relationships regarding their behavioural intention to use the radar visualisation tool to understand student performance. Figure 2 presents the structural model (main model) results for the parent group, with standardised path coefficients shown for each relationship. Figure 3 presents the corresponding results for the student group.

Table 11. Path analysis results for the parent group (overall model).

Paths	Estimate (β)	S.E.	<i>t</i>	<i>p</i>
PE→CI	0.249	0.050	5.189	***
EE→CI	−0.253	0.080	−3.140	0.002 **
SI→CI	0.192	0.110	1.991	0.046 *
FC→CI	0.801	0.145	5.832	***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12. Path analysis results for the student group (overall model).

Paths	Estimate (β)	S.E.	<i>t</i>	<i>p</i>
PE→CI	0.038	0.181	0.250	0.802
EE→CI	−0.422	0.243	−1.790	0.074
SI→CI	−0.461	0.205	−2.350	0.019 *
FC→CI	1.755	0.402	4.622	***

* $p < 0.05$, *** $p < 0.001$.

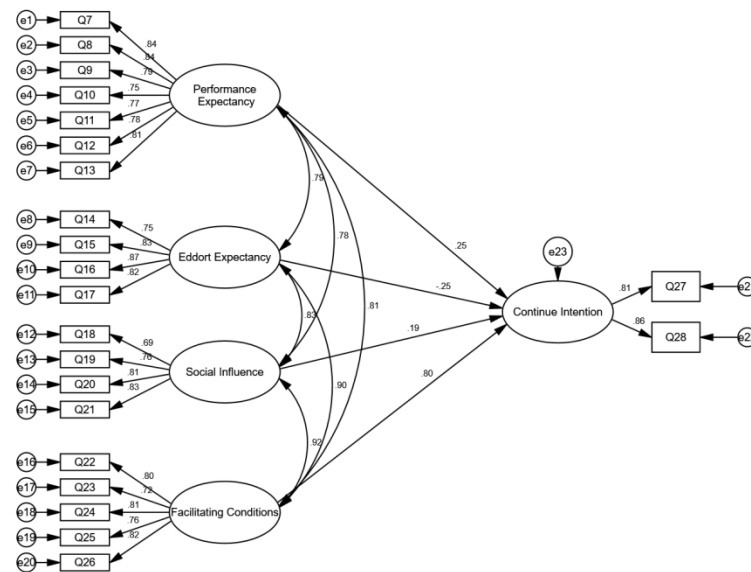


Figure 2. Structural equation model for the parent group.

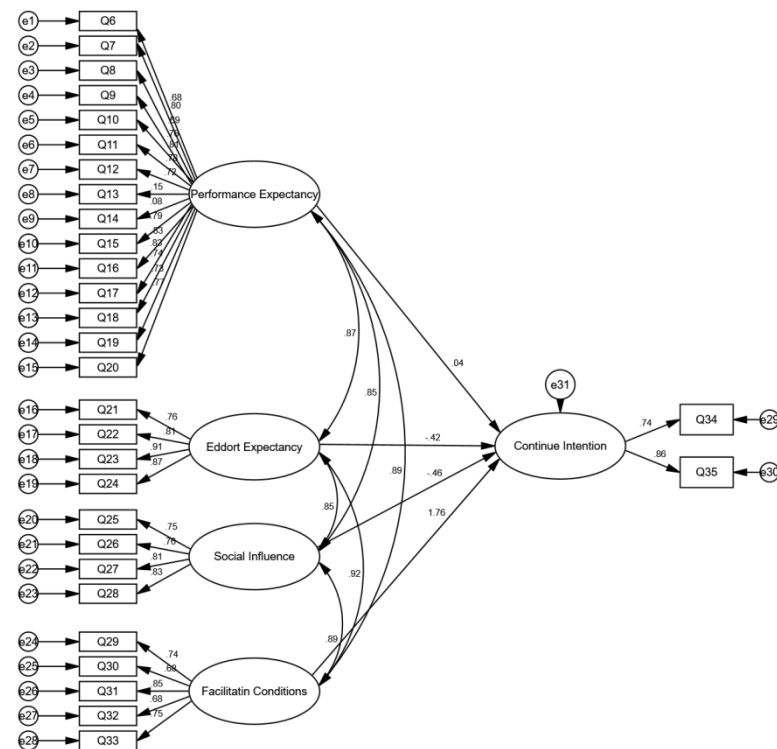


Figure 3. Structural equation model for student group.

For the parent group, PE had a significant and positive effect on CI ($\beta = 0.249$, $t = 5.189$, $p < 0.001$), indicating that parents were more willing to support or continue the use of radar visualisation tool when they perceived performance-related benefits for their child. EE was also significant but negatively associated with CI ($\beta = -0.253$, $t = -3.140$, $p = 0.002$), suggesting that higher perceived effort may discourage intention in the parental context. In addition, SI positively predicted CI ($\beta = 0.192$, $t = 1.991$, $p = 0.046$), implying that parents' decisions to adopt such tools may be influenced by others, such as teachers, other parents, or families. Finally, FC showed a strong effect ($\beta = 0.801$, $t = 5.832$, $p < 0.001$), demonstrating that access to relevant resources, support or information greatly strengthens parents' adoption intention.

For the student group, the model revealed two significant predictors of CI. FC exerted a strong positive effect on CI ($\beta = 1.755$, $t = 4.622$, $p < 0.001$), indicating that access to technological or instructional support considerably enhanced students' willingness to continue using the radar visualisation tool. Conversely, SI showed a significant negative effect on CI ($\beta = -0.461$, $t = -2.350$, $p = 0.019$), suggesting that peer or social comparison pressure may reduce students' intention to use the tool. PE ($\beta = 0.038$, $t = 0.250$, $p = 0.802$) and EE ($\beta = -0.422$, $t = -1.790$, $p = 0.074$) were not significant predictors, indicating that perceived benefits and ease of use did not substantially drive students' adoption intention in the model.

Overall, the structural model results indicated that FC was the strongest and most consistent predictor of CI across both groups, whereas PE and EE showed group-specific effects. Notably, SI demonstrated opposite directional effects for students and parents, suggesting potentially different motivational mechanisms underlying their adoption behaviours. These structural results provided the basis for subsequent multi-group comparison analyses to examine whether the observed differences are statistically significant across groups.

5.5. Structural Relationship Patterns Across Groups (Descriptive Comparison)

Since the parent and student group questionnaires were not identical, measurement invariance could not be established, and a formal multi-group SEM was therefore not appropriate. Instead, the structural models were estimated separately for parents and students, and the resulting path patterns were compared descriptively to examine whether the predictive mechanisms differed across stakeholder roles.

This comparison examined the pattern of significant paths and direction of effects identified within each group, emphasising substantive patterns over statistical test coefficient differences. Table 13 summarises this pattern comparison, indicating whether each path was significant (positive or negative) in the respective group and whether the overall pattern suggested similarity or divergence across the two stakeholder populations.

Table 13. Cross-group descriptive comparison.

Paths	Parent Group	Student Group	Pattern Difference
PE→CI	Significant (+)	Non-significant	Divergent
EE→CI	Significant (+)	Non-significant	Divergent
SI→CI	Significant (+)	Significant (-)	Consistent ¹ (Opposite Direction)
FC→CI	Significant (+)	Significant (+)	Consistent

¹ Both groups showed significant effects with comparable magnitudes.

To address RQ1, a descriptive comparison was conducted to examine whether structural relationships differed between parents and students. The results showed that the PE→CI and EE→CI paths showed statistically significant cross-group differences; both predictors were significant for the parent group but non-significant for students, indicating that PE- and EE-related perceptions played a meaningful role only in the parent group.

For the SI→CI path, both groups showed significant effects but in opposite directions. Students exhibited a significant negative effect, whereas parents showed a significant positive effect; the directional reversal suggests that SI functioned differently across the two groups, although no significant difference in effect magnitude was detected. Finally, the FC→CI path was positive and significant in both groups, and no significant difference was found, indicating that facilitating conditions served as a common driver of continued intention.

Overall, this comparison indicated that parents' adoption intention was shaped by PE- and EE-related beliefs, whereas students' adoption intention was not directly explained by

these factors. In contrast, FC was a consistent predictor for both groups, and SI operated divergently across the two populations.

5.6. Moderation Analysis

To further examine whether the structural relationships varied across subgroups within each group, multi-group SEM was conducted for a set of demographic and experience moderators within the student and parent samples. The moderators examined included gender, age, educational level, child's year of study, frequency of parent–child discussion on academic, and prior usage experience for both groups.

For the parent group, subgroup analyses showed that communication frequency with children moderated all four structural paths, with stronger and more significant effects observed in the high-frequency communication subgroup. The PE→CI path also showed significance among parents whose children were in different years of study, but the remaining paths showed no significant moderating effects. The other moderators did not produce significant moderating effects on the structural paths, as both paths and cross-group comparisons remained stable across subgroups.

For the student group, the results indicated that grade level moderated the FC→CI path, with the effect being significant and stronger among F4–F6 students compared to F1–F3 students. The SI→CI path also showed significance among high school students but not among middle school students. In contrast, gender, educational attainment goals, frequency of parent–child discussions on academics, and prior usage experience did not exert moderating effects on any of the structural paths, as the difference tests across subgroups were non-moderated.

Across both groups, only a limited number of moderators produced detectable differences in the structural relationships. Frequency of parent–child discussion on academics served as a relevant moderator for parents, whereas year of study emerged as a relevant moderator for students, while other demographic and experience-related characteristics did not alter the structural relationships in a significant manner. Detailed information is presented in Tables 14 and 15.

Table 14. Path analysis results for the parent group by moderator variables.

Moderators	Options	Path	Estimate
Gender	Male	PE→CI	0.234 **
		EE→CI	−0.218
		SI→CI	−0.100
		FC→CI	1.073 **
	Female	PE→CI	0.299 ***
		EE→CI	−0.356 **
		SI→CI	0.285 **
		FC→CI	0.763 ***
Age	≤50	PE→CI	0.256 ***
		EE→CI	−0.274 *
		SI→CI	0.031
		FC→CI	0.972 ***
	>50	PE→CI	0.175 *
		EE→CI	−0.199 *
		SI→CI	0.439 **
		FC→CI	0.580 ***

Table 14. Cont.

Moderators	Options	Path	Estimate
EdLevel	Secondary School or Below	PE→CI	0.273 ***
		EE→CI	−0.219 *
		SI→CI	0.237 *
		FC→CI	0.702 ***
	Undergraduate or Above	PE→CI	−1.498
		EE→CI	−1.594
		SI→CI	−3.140
		FC→CI	6.840
Child's Year of Study	F1–F3	PE→CI	0.418 ***
		EE→CI	−0.268
		SI→CI	0.187
		FC→CI	0.737 ***
	F4–F6	PE→CI	0.163 **
		EE→CI	−0.210 *
		SI→CI	0.145
		FC→CI	0.873 ***
Freq	Low Frequency	PE→CI	0.193
		EE→CI	−0.098
		SI→CI	0.505 **
		FC→CI	0.405 *
	Mid-High Frequency	PE→CI	0.277 ***
		EE→CI	−0.315 **
		SI→CI	0.061
		FC→CI	0.964 ***
Experience	General Experience	PE→CI	0.242 **
		EE→CI	−0.235 *
		SI→CI	0.219
		FC→CI	0.765
	High Experience	PE→CI	0.252 ***
		EE→CI	−0.277
		SI→CI	0.169
		FC→CI	0.842 **

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 15. Path analysis results for the Student group by moderator variables.

Moderators	Options	Path	Estimate
Gender	Male	PE→CI	0.123
		EE→CI	−0.546
		SI→CI	−0.523 *
		FC→CI	1.848 ***
	Female	PE→CI	0.060
		EE→CI	−0.178
		SI→CI	−0.336
		FC→CI	1.382 **

Table 15. Cont.

Moderators	Options	Path	Estimate
Year of Study	F1–F3	PE→CI	0.640 **
		EE→CI	0.349
		SI→CI	−0.041
		FC→CI	0.045
	F4–F6	PE→CI	−0.337
		EE→CI	0.164
		SI→CI	−0.416 *
		FC→CI	1.495 ***
Goals	Completing Secondary School or Below	PE→CI	2.456
		EE→CI	−2.575
		SI→CI	−8.817
		FC→CI	9.980
	Completing Bachelor Degree	PE→CI	−0.369
		EE→CI	−0.123
		SI→CI	−0.346
		FC→CI	1.776 *
	Completing Postgraduate Degree or Above	PE→CI	1.637
		EE→CI	0.277
		SI→CI	0.158
		FC→CI	−1.034
Freq	Low Frequency	PE→CI	−0.012
		EE→CI	−0.174
		SI→CI	−0.899
		FC→CI	1.853 ***
	Mid-High Frequency	PE→CI	0.133
		EE→CI	−0.447
		SI→CI	−0.318
		FC→CI	1.617
Experience	General Experience	PE→CI	0.259
		EE→CI	−0.209
		SI→CI	−0.163
		FC→CI	1.084 ***
	High Experience	PE→CI	0.042
		EE→CI	−0.258
		SI→CI	−0.265
		FC→CI	1.371 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.7. Hypothesis Testing

In this research, several moderators were considered to evaluate their impact on the research model, with hypotheses H1 to H7 serving as the focus. The results indicated that the structural hypotheses were partially supported in the two groups, and the moderating hypotheses were supported in the parent group but only partially supported in the student group. A summary of the hypothesis testing results is presented in Table 16.

Table 16. Hypothesis testing results.

	Hypotheses	Parent Group Results	Student Group Results
H1	Gender significantly moderates the structural relationships in the research model.	Not Supported	Not Supported
H2	Usage experience significantly moderates the structural relationships in the research model.	Not Supported	Not Supported
H3	Students' year of study significantly moderates the structural relationships in the research model.	Partially Supported	Partially Supported
H4	Frequency of parent–child discussions on academics significantly moderates the structural relationships in the research model.	Supported	Not Supported
H5	Age significantly moderates the structural relationships in the research model.	Not Supported	N/A
H6	Parents' educational level significantly moderates the structural relationships in the research model.	Not Supported	N/A
H7	Students' educational attainment goals significantly moderate the structural relationships in the research model.	N/A	Not Supported
H8	Performance expectancy significantly affects continued intention to use the visualisation tool.	Supported	Not Supported
H9	Effort expectancy significantly affects continued intention to use the visualisation tool.	Supported	Not Supported
H10	Social influence significantly affects continued intention to use the visualisation tool.	Supported	Supported
H11	Facilitating conditions significantly affect continued intention to use the visualisation tool.	Supported	Supported

6. Discussion

6.1. Interpretation of Perceived Differences from Parents and Students

The findings reveal clear differences in how parents and students interpret and evaluate the radar visualisation tool. The radar visualisation tool was iteratively designed based on focus group suggestions from relevant educational stakeholders, ensuring that it addressed functional, usability and psychological needs in actual education scenarios. Although both parent and student groups interacted with the same visualisation tool and information in this study, the analysed results indicate that they did not perceive the tool in the same way nor use it for the same purposes.

The separate SEM analyses and perception differences consistently indicate that parents and students engaged with the same information through different interpretive perspectives. Parents used the radar visualisation primarily as decision-supporting information to understand their child's academic progress and plan further educational directions, while students considered the radar visualisation tool to be more closely associated with evaluation and external monitoring. Given this, the visualisation tool should be understood as both a learning support tool and an educational communication medium whose meaning is shaped by stakeholder roles.

For parents, continued intention to use the visualisation was associated with multiple evaluative considerations. PE shows a significant positive relationship with continued intention, suggesting that parents were primarily concerned with whether the visualisation helped them understand their child's academic performance. SI was also significant and positive, indicating that parents' willingness to continue using the tool was reinforced by

expectations from teachers, the school, or other parents. FC further supported continued use, meaning that the concepts of perceived behavioural control, facilitating conditions and compatibility increased parental engagement. Interestingly, EE showed a significant negative relationship with continued intention. This suggests that parents did not evaluate the tool primarily based on usability convenience. In educational settings where parents are seeking meaningful insights into their child's academic progress, perceived interpretability and informational value may outweigh operational simplicity [48]. This suggests that for parent stakeholders, the tool's credibility as a decision-support resource may be more salient than its ease of use.

Students demonstrated a markedly different evaluation perspective. PE and EE did not significantly influence their continued intention to use the visualisation, indicating that neither perceived usefulness nor perceived ease of use determined their willingness to engage with the visualisation tool. Instead, FC emerged as the strongest positive predictor, suggesting that students' engagement depended strongly on whether the visualisation was readily accessible and supported within their learning environment. More notably, SI showed a significant negative relationship with continued intention. The negative SI effect indicates that social expectations did not encourage engagement but instead discouraged continued use. This finding is consistent with recent research on learning analytics acceptance among secondary students. In the study of Martens et al. on 277 secondary school students in Flanders, the authors similarly found that social influence was not a significant predictor of acceptance for students, whereas it was significant for parents [49]. They suggest that when performance visualisations are associated with external monitoring or evaluative purposes, students may perceive them as surveillance rather than support, reducing their willingness to engage. This interpretation aligns with a self-determination theory perspective, which posits that externally imposed expectations can undermine intrinsic motivation when they are perceived as controlling rather than autonomy-supportive [50].

This pattern is consistent with prior studies showing that different educational stakeholders interpret academic performance according to their roles and responsibilities. For example, a study from Sahin and Ifenthaler edited volume on learning analytics visualisations emphasises that students and parents often have fundamentally different interpretive frameworks when engaging with the same performance data [51]. Similarly, Saia found that within multi-tiered support systems, teachers, administrators, and specialists each prioritised different aspects of visualised data based on their professional responsibilities [52]. Overall, these findings address RQ1 by indicating that parents and students exhibited different behavioural patterns in how continued intention was formed when engaging with the same visualisation.

6.2. Continued Intention and Engagement Differences Between Parents and Students

Beyond perceptual differences, the findings provide important insights into parents' and students' continued intention to engage with the visualisation tool. The Mann–Whitney U test revealed that parents reported significantly higher continued intention than students. This behavioural difference corresponded closely with the observed group differences in performance expectancy and social influence, while no differences were found in effort expectancy and facilitating conditions.

This pattern is theoretically meaningful within the UTAUT model. In technology acceptance research, behavioural intention is primarily driven by perceived usefulness and social endorsement as established in the foundational UTAUT model [6]. Meta-analytic reviews have confirmed that these relationships hold across diverse educational technology contexts, though their relative strength may vary by user group and setting [53,54]. Parents perceived the visualisation information as more beneficial for academic planning and

were also more influenced by external expectations from schools and educational norms. As a result, they demonstrated a stronger intention to continue using the system. In contrast, although students did not perceive the system as more difficult to use and had comparable access conditions, they were less convinced of its personal relevance to their immediate learning experience. This interpretation aligns with research on task–technology fit [55] and personal meaningfulness in learning analytics [56]. Jivet et al. argue that for students to engage with learning dashboards, the information must be perceived as personally meaningful and actionable for their immediate learning goals, rather than merely informative for future planning.

The findings therefore suggest that continued engagement with educational visualisation systems is not determined mainly by operational ease or technical support. Instead, it depends on whether users interpret the information as consequential for future academic pathways. For parents, the visualised predictions directly supported long-term educational planning, making the system a decision-support tool. For students, however, the information was more abstract and future-oriented, and thus less strongly connected to their present academic activities.

This suggests that while both groups encounter the same information, their engagement with it is fundamentally distinct. Parents are more inclined to revisit the visualisation tool as part of sustained educational decision-making, whereas students may perceive it as informational feedback rather than actionable directions. Therefore, sustained use of predictive educational visualisation systems may rely less on improving usability and more on enhancing students' perceived personal relevance and interpretability of the information. These findings directly address RQ2 by showing that continued intention to use the visualisation system is shaped by perceived decision for both parents and students, above and beyond considerations of usability alone. Parents' intention was driven by the system's value for academic planning and social expectations, whereas students' intention depended on whether the information was interpreted as personally meaningful for their present learning. Therefore, the adoption of educational performance visualisation is shaped by both technological acceptance factors and the roles stakeholders play in educational decision-making. Overall findings align with research indicating that parents are typically more motivated to engage with academic performance information than students, as such information directly supports their supervisory and decision-making roles. Martens et al. similarly found that parents reported significantly higher performance expectancy and behavioural intention compared to students when considering learning analytics systems [49]. They attribute this difference to parents' position as secondary users who experience the consequences of the technology indirectly, whereas students are primary targets who may feel subjected to evaluation.

6.3. Theoretical Contributions

This study applies the UTAUT model to an educational performance visualisation tool and clarifies how the model operates in this specific form of technology use. While UTAUT has been widely employed in educational research, it has primarily been examined in the context of learning systems such as e-learning platforms and mobile learning applications [57,58]. This present study instead applies UTAUT to investigate a visualisation designed for interpreting academic performance. The results indicate that the UTAUT model remains applicable in this context, but the relationships underlying continued intention differ from those typically observed in system usage settings. In particular, students' continued intention was not significantly associated with PE, suggesting that students' engagement was not primarily based on expectations that the visualisation would directly enhance their academic performance. This finding is consistent with recent studies of

learning analytics acceptance among students. Martens et al. also found that for secondary students considering a grade-prediction system, performance expectancy was not the primary driver of acceptance [49]. They suggest that students may evaluate such systems through a different cognitive lens than adults, one focused more on immediate feedback and social comparison than on future performance gains. This finding indicates that technology acceptance in educational visualisation environments depends more on the contextual meaning and situational relevance than on conventional perceptions of usefulness. These findings suggest that technology acceptance in educational visualisation contexts should not be interpreted solely as system adoption, but as interpretation of information. In other words, stakeholders are not primarily adopting a technological tool, but instead engaging with performance information communicated through a visual representation. This shifts the role of UTAUT constructs from predicting technology usage to explaining how different users make sense of learning analytics information.

The divergent patterns between parents and students can be further theorised through complementary psychological frameworks. From a role theory perspective, parents and students occupy fundamentally different positions within the educational relationship. Parents act as supervisors responsible for monitoring academic progress [59], making the visualisation a decision-support tool, which explains why performance expectancy strongly predicts their continued intention. Students, as the primary agents directly engaged in learning, may perceive the same visualisation not as a tool they use, but as a representation of how they are being evaluated [56].

This interpretation aligns with self-determination theory [50]: when external tools are perceived as controlling rather than autonomy-supportive, they can undermine intrinsic motivation. For students, social expectations may trigger psychological reactance [60], explaining the negative effect of social influence. For parents, the same expectations function as normative support reinforcing engagement [61]. Thus, a key theoretical contribution of this study lies in demonstrating that technology acceptance in educational visualisation is not merely about system adoption, but about how users' roles and psychological needs shape their interpretation of performance information.

Another contribution concerns the roles of participants in technology acceptance. While both parents and students engaged with the same visualisation tool, the results revealed markedly divergent acceptance pathways. These differences transcend mere demographic variation; rather, they underscore how an individual's role within the educational relationship fundamentally shapes the operationalisation of core UTAUT constructs. Parents evaluated the visualisation as an informational resource supporting understanding of academic progress, whereas students' engagement was influenced primarily by contextual accessibility. This finding suggests that UTAUT should not be treated as a uniform behavioural model in educational environments. The relationships between PE, EE, SI, FC and CI may be role-dependent. By incorporating multiple stakeholder groups within a single educational setting, this study highlights the importance of considering relational roles when applying technology acceptance models in education.

Furthermore, the study provides insight into the interpretation of SI within learning analytics visualisation tool. While SI is typically associated with increased technology adoption in the original UTAUT model [6] and many educational contexts [62], the negative relationship observed among students indicates that external expectations do not necessarily promote voluntary engagement. This finding resonates with research on reactance theory [60], which suggests that when individuals perceive external pressures as threatening their autonomy, they may respond by rejecting the advocated behaviour. In educational settings, students may interpret teacher- or school-endorsed tools as extensions of evaluative structures rather than as resources for personal learning, leading to resistance

rather than acceptance [63]. This suggests that transparency-oriented tools do not automatically increase user engagement and that the motivational meaning attached to performance information can alter behavioural responses. Consequently, the study expands existing understanding of technology acceptance by showing that the direction and impact of social influence may vary depending on whether the technology supports task completion or performance interpretation.

6.4. Educational Implications

The findings suggest that the academic performance visualisation tool should not be treated as a single-purpose reporting interface. This is because parents and students interpreted the same information through different perspectives. Parents primarily viewed the visualisation as a tool for understanding academic standing and supporting educational planning, whereas students responded to whether the information was personally understandable and relevant to their own learning. In practice, visualisation therefore functions simultaneously as a communication medium for parents and as a reflective learning aid for students.

While comparative indicators are commonly assumed to motivate learners, the results suggest that students may perceive peer reference primarily as evaluative feedback instead of guidance for action. Continued engagement therefore depends on whether the meaning of the information is interpreted as relevant for personal learning. In this sense, the adoption of the visualisation is shaped by how users interpret the information, extending beyond visual design alone. Another implication concerns the importance of FC. Continued engagement depended on interface usability and the ability of users to access and interpret information within everyday school routines. Stable access, clear navigation, and integration with existing parent communication channels and classroom practices are therefore essential. Short orientation sessions or guided demonstrations may substantially improve sustained use.

Generally, the findings highlight the importance of psychological safety in performance visualisation tools. For students, the visualisation tool should foreground progress, learning goals, and actionable feedback, with less emphasis on ranking. For parents, the presentation of performance trends should be oriented toward constructive planning instead of pressure. When visualisations are designed as a supportive learning aid rather than a monitoring, they are more likely to encourage sustainable engagement among both groups.

These recommendations align with broader principles of user-centred design in learning analytics [51] and with research emphasising the importance of psychological safety in educational technology implementation.

6.5. Limitations and Further Research

Despite the mentioned contributions of this study, several limitations should be acknowledged to inform further research. This study adopted purposive sampling from a single secondary school in Macao. Although the setting allowed consistent access to both parents and students using the same visualisation tool, the finding may not be fully generalisable to other educational systems or cultural contexts. Further research could examine similar visualisation practices across schools with different curricula, assessment practices or parental involvement patterns.

Regarding the measurement model, two limitations should be noted. First, two items within the PE of the student group construct exhibited factor loadings below the recommended threshold. These items were retained to preserve content validity [47], and the construct's composite reliability and average variance extracted remained above acceptable levels [30]. However, future research should consider refining these items or developing

more developmentally appropriate measures for adolescent respondents. Second, the discriminant validity between facilitating conditions and effort expectancy in the student group showed a slight issue, with the inter-construct correlation (0.808) exceeding the square root of the AVE for FC (0.796). This suggests that students may perceive these constructs as conceptually similar, possibly because ease of use and available support are closely related in their integrated learning environment [47]. Future research could employ more fine-grained measures to better distinguish these constructs for students.

Accordingly, the present findings are confined to explaining behavioural intention and do not extend to predictions of actual technology usage. The data obtained were based on participants' self-reported perceptions and behavioural intentions rather than observed behavioural usage. While continued intention is an established construct in technology acceptance research, self-reported measures may be affected by response tendencies or social desirability bias. Longitudinal research incorporating behavioural log data, actual access frequency, or follow-up usage tracking would provide stronger evidence regarding sustained engagement with performance visualisation tools.

The response sizes of the two groups were unbalanced, with more parent responses than student responses. Although non-parametric tests were conducted to reduce analytical bias, the unequal group sizes may still have influenced statistical sensitivity when interpreting comparative analysis.

Moreover, the results indicated differential explanatory power across the two groups, suggesting that the UTAUT model may not fully capture the factors influencing students' intention in using visualisations. Future research may therefore incorporate constructs such as learning motivation, feedback interpretation, or academic self-concept to better explain student behaviour. Previous studies have demonstrated the value of integrating UTAUT with self-determination theory to capture motivational dimensions that traditional acceptance models may overlook [64].

Furthermore, the current design presented data from the current and previous terms without a clear temporal transition, which may have limited the effectiveness of the tool in showing performance progression. Future iterations could include features that visualise change over time to encourage active engagement and maximise the utility of radar visualisation tools.

Lastly, the study focused specifically on radar visualisation without comparing its effectiveness to other types of visualisation tools. Radar visualisation enables compact presentation of multi-subject performance, but the finding should not be interpreted as applying to all types of educational visualisation. Future research is needed to explore broader applications and alternative visualisation formats.

7. Conclusions

This study explored the acceptance of and continued intention to use a radar visualisation tool designed to present multi-subject academic performance, with the tool iteratively developed to address the interpretive needs of diverse educational stakeholders. Parents and students are two groups that share the same performance data but hold distinct roles in the learning process. By engaging both groups, this research provides empirical evidence that a visualisation functions not merely as a reporting interface but as a critical communication medium whose meaning is actively constructed by users.

The findings reveal fundamentally different patterns of continued engagement across the two groups. For parents, the tool served as a decision-support information for academic planning, proving valuable in tracking students' academic progress, identifying strengths and weaknesses, and facilitating discussions with their child. In contrast, students' continued intentions were influenced by social and contextual factors surrounding its use,

reflecting concerns related to comparison pressure and external expectations. FC emerged as the only consistent positive factor of continued intention across both groups.

A key contribution of this study is the development and evaluation of a visualisation tool that simultaneously addresses the interpretive needs of parents and students. By examining two groups who interacted with the same tool, this study extends the current understanding of how radar visualisation can function in real-world educational contexts. Aligned with RQ1 and RQ2, the findings revealed a divergence between parents and students both in their evaluation of the visualisation and in their stated intention toward continued use. Overall, the findings highlight the effectiveness of radar visualisations for parents while underscoring opportunities to enhance student engagement through tailored designs that prioritise agency and meaningful feedback and reduce comparison anxiety. By addressing these aspects, the visualisation tool can better support productive academic communication between parents and students, thereby fostering more sustained and meaningful use in real-world educational environments.

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Informed Consent Statement: Relevant information was provided in the survey; informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to parents' and students' privacy reasons.

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Abbreviations

The following abbreviations are used in this manuscript:

UTAUT	Unified Theory of Acceptance and Use of Technology
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
CI	Continued Intention
SEM	Structural Equation Modelling

Appendix A. Designed Questionnaires for Parents

The questions designed for parents are shown below. The whole questionnaire includes 29 items. Questions 1 to 5 collect some general demographic data, while Q6 to 28 are designed as 5-point Likert scales to measure opinions, ranging from 1 (strongly disagree) to 5 (strongly agree). Q29 is an open-ended question for collecting extra ideas if needed. The questions are listed below.

1. Gender
2. Age
3. Education Level
4. Grade Level of their Child
5. Frequency of Discussing Academic-oriented Matters with Child
6. I have prior experience viewing academic rankings and using radar charts (also known as spider charts) to analyse grades.
7. I believe that using this supplementary visualisation tool to understand my child's grades is very effective.
8. This supplementary visualisation tool allows me to quickly understand my child's grades.
9. This supplementary visualisation tool allows me to quickly improve my efficiency.
10. This supplementary visualisation tool allows me to quickly and clearly understand my child's grade ranking.
11. This supplementary visualisation tool allows me to quickly and clearly understand the strengths and weaknesses of my child's grades, as well as the differences compared to other students.
12. This supplementary visualisation tool can help me and my child set next learning goals.
13. Using this supplementary visualisation tool increases my opportunities to understand my child's grades.
14. In my perspective, becoming proficient in reading this supplementary visualisation tool would be easy.
15. I believe the design and content of this supplementary visualisation tool are clear and easy to understand.
16. I believe this supplementary visualisation tool is easy to use.
17. Learning how to interpret the information in this supplementary visualisation tool is very easy for me.
18. People who influence my behaviour (e.g., school teachers, other parents) think that I should use this supplementary visualisation tool to understand my child's academic performance.
19. People who are important to me (e.g., family members) think that I should use this supplementary visualisation tool to understand my child's academic performance.
20. The school provides assistance for parents to read/understand this supplementary visualisation tool.
21. Overall, I feel that the school supports me in reading/using this supplementary visualisation tool.
22. I have the necessary support to read/understand this supplementary visualisation tool.
23. I can understand and read this supplementary visualisation tool on my own.
24. Using this supplementary visualisation tool adequately addresses my need to understand my child's academic performance.
25. When I encounter difficulties using this supplementary visualisation tool, I can get appropriate explanations or help.
26. I believe the information provided by this supplementary visualisation tool meets my needs.

27. I would recommend other parents use this supplementary visualisation tool to understand their children's academic performance.
28. Overall, I intend to continue using this supplementary visualisation tool in the future to understand my child's academic performance.
29. We welcome your suggestions for improving the content and format of this supplementary visualisation tool (e.g., what information should be added or removed, etc.).

Appendix B. Designed Questionnaires for Students

The questions designed for students are shown below. The whole questionnaire includes 36 items. Questions 1 to 4 collect some general demographic data, while Q5 to 35 are designed as 5-point Likert scales to measure opinions, ranging from 1 (strongly disagree) to 5 (strongly agree). Q36 is an open-ended question for collecting extra ideas if needed. The questions are listed below.

1. Gender
2. Current Grade Level
3. Educational Attainment Goals
4. Frequency of Discussing Academic-oriented Matters with Parents (or guardians)
5. I have prior experience viewing my academic rankings and using radar charts (also known as spider charts) to analyse my grades.
6. I believe that a supplementary visualisation tool format can effectively show the differences between my own grades and those of other students.
7. I believe that presenting grades using radar visualisation is very effective for me.
8. I believe that presenting grades using numerical formats is very effective for me.
9. I believe that using this supplementary visualisation tool to understand my own grades is very effective.
10. This supplementary visualisation tool allows me to quickly understand my own grades.
11. This supplementary visualisation tool helps me understand my own strengths and weaknesses.
12. I believe that understanding my grade ranking can help motivate my learning.
13. I believe that understanding my grade ranking will bring me pressure.
14. I believe that understanding my grade ranking will lead to a negative attitude towards learning.
15. This supplementary visualisation tool allows me to quickly improve the efficiency of understanding my own grades.
16. This supplementary visualisation tool allows me to quickly and clearly understand my grade ranking.
17. This supplementary visualisation tool allows me to quickly and clearly understand the strengths and weaknesses of my grades, as well as the differences compared to my classmates.
18. This supplementary visualisation tool helps me identify my potential for development within my relevant group (e.g., whole grade level, arts/sciences stream).
19. This supplementary visualisation tool effectively helps me set my next learning goals.
20. Using this supplementary visualisation tool increases my opportunities to understand my own grades.
21. In my perspective, becoming proficient in reading this supplementary visualisation tool would be easy.
22. I believe the design and content of this supplementary visualisation tool are clear and easy to understand.
23. I believe this supplementary visualisation tool is easy to use.

24. Learning how to interpret the information in this supplementary visualisation tool is very easy for me.
25. People who influence my behaviour (e.g., school teachers, classmates) think that I should use this supplementary visualisation tool to understand my academic performance.
26. People who are important to me (e.g., parents/guardians) think that I should use this supplementary visualisation tool to understand my academic performance.
27. The school provides assistance for students to read/understand this supplementary visualisation tool.
28. Overall, I feel that the school supports me in reading/using this supplementary visualisation tool.
29. I have the necessary support to read/understand this supplementary visualisation tool.
30. I can understand and read this supplementary visualisation tool on my own.
31. Using this supplementary visualisation tool adequately addresses my need to understand my own academic performance.
32. When I encounter difficulties using this supplementary visualisation tool, I can get appropriate explanations or help.
33. I believe the information provided by this supplementary report can meet my needs.
34. I would recommend other students use this supplementary visualisation tool to understand their academic performance.
35. Overall, I intend to continue using this supplementary visualisation tool in the future to understand my academic performance.
36. We welcome your suggestions for improving the content, format, or other aspects of this supplementary visualisation tool (e.g., what information should be added or removed, etc.).

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