

# Risk Points

A Transparent No-Configuration  
Statistical Risk Model



## Introduction

In the evolving landscape of educational technology and learning analytics, identifying and managing student risks is paramount to ensuring academic success. IntelliBoard's Risk Points model offers a transparent, non-configuration statistical approach to assessing student risks. Risk Points is a statistical method designed to compare learners' engagement and performance to their peers within the same course, delivering insights without requiring historical data or manual configuration. This paper discusses the technical architecture, advantages, and potential applications of the Risk Points model in comparison to traditional risk assessment methodologies.

## Background: Traditional Risk Reporting Models

Previously, IntelliBoard has offered two primary methods for determining student risk:

### *Rules-Based Models*

Configured using if-then rules with custom thresholds, these models are flexible and account for differences between learners and contexts but require manual setup by administrators or instructors with extensive knowledge of metrics and thresholds. Learners are evaluated using defined benchmarks

```
IF(({Expected Activities/Day Simplified})  
>COALESCE(({Actual Activities/Day}),0),0,1)
```

Figure 1: Example of rule-based risk model

### *Machine Learning Models:*

Utilizing historical student data, machine learning models use algorithms to adjust thresholds computationally and provide more accurate risk predictions through the analysis of large datasets (including interactions between risk factors) without requiring manual configuration. IntelliBoard supports multiple algorithms without requiring coding skills on the part of clients. Learners are evaluated in comparison to their peers in the past.

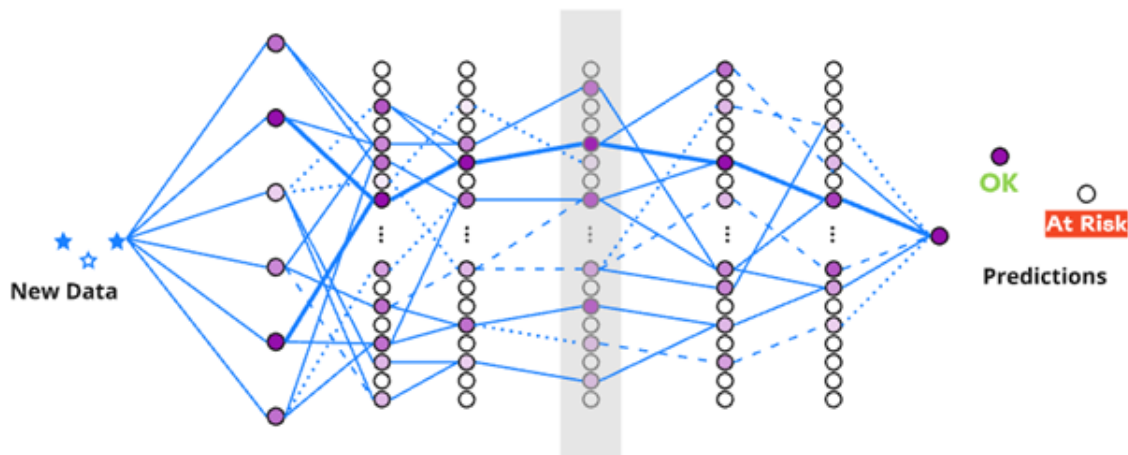


Figure 2: Machine Learning predictive model

These methods have served our clients well. However, each of these models also has limitations. Rule-based systems require a detailed local understanding of the factors affecting risk and can require considerable custom configuration. Results are calculated at run-time for each report, sometimes slowing performance, and history is not saved, limiting support for trend analysis.

Meanwhile, machine learning models require extensive historical data to function effectively and must be tested for accuracy and specificity. Results are saved for future reports and trend analysis. For many of our clients, sufficient historical data may not be available to train a strong model when IntelliBoard is first implemented, as some of the most useful data points are calculated within IntelliBoard itself after connection.

A single machine learning model based on the raw metrics available from the LMS and other connected systems may not be a good fit for all learners or courses at an institution, as cohorts or programs may have significant distinctive characteristics. IntelliBoard supports training multiple machine learning models; the additional effort to partition data and train and test multiple models can seem overwhelming.

## Risk Points: A No-Configuration Approach

The introduction of Risk Points bridges the gap between flexibility, accuracy, and convenience. It is a statistical comparison method whereby learners are compared to their peers within the same course based on several metrics, including engagement, attendance, and course progress. Unlike IntelliBoard's other risk models, Risk Points do not require historical data or manually set benchmarks, instead comparing learners to their peers in the present. This allows for immediate implementation and continuous updates via nightly snapshots, supporting trend analysis.

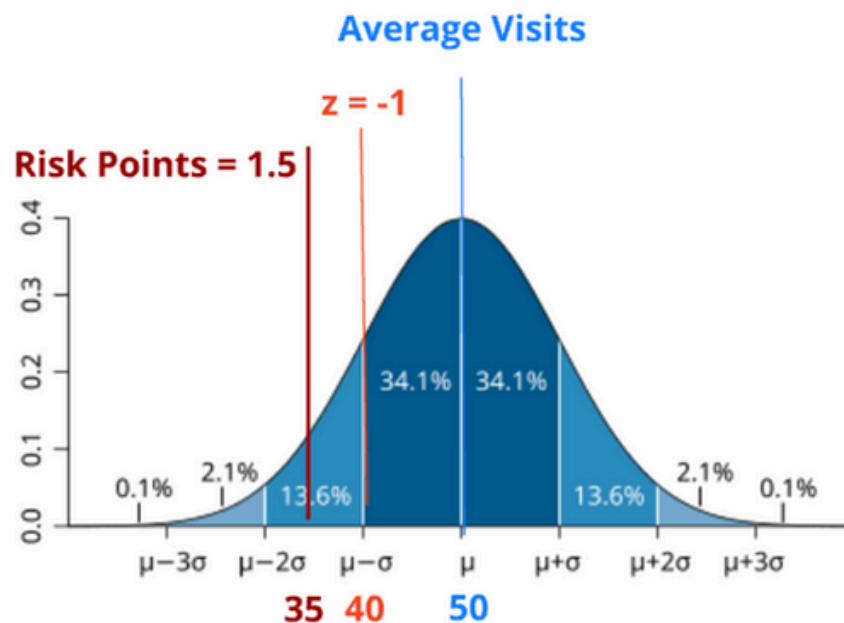


Figure 3: Risk Points are based on a statistical comparison to the learner's peers in the same course.

## Key Advantages of Risk Points

- **No Configuration** – Institutions can deploy Risk Points without custom setup, eliminating the complexity associated with manually defining rules and benchmarks or training and evaluating machine learning models.
- **Peer Comparison** – Learners' performance is compared to their immediate peers using the statistical method of Z-scores (Abdi, 2007), providing a clear understanding of where a student stands relative to others in the same course. This comparison takes variation into account and defines risk based on significant differences from peer means. Risk points are assigned based on the unit of standard deviations.
- **Transparency** – All metrics and calculations used in Risk Points are completely transparent to learners, instructors, and other stakeholders. All inputs and calculations can be reproduced in reports, if desired.
- **Automated Data Capture** – Metrics are captured and stored in nightly snapshots\*, which enable trend analysis and allow for historical comparisons over time.
- **Performance** – Because Risk Points are calculated as part of nightly processing, reports are not burdened with extensive on-the-fly calculations.
- **Inclusion in Default Reports** – Risk Points are incorporated into our persona-based default reports and dashboards, ready to use on day one of an implementation.

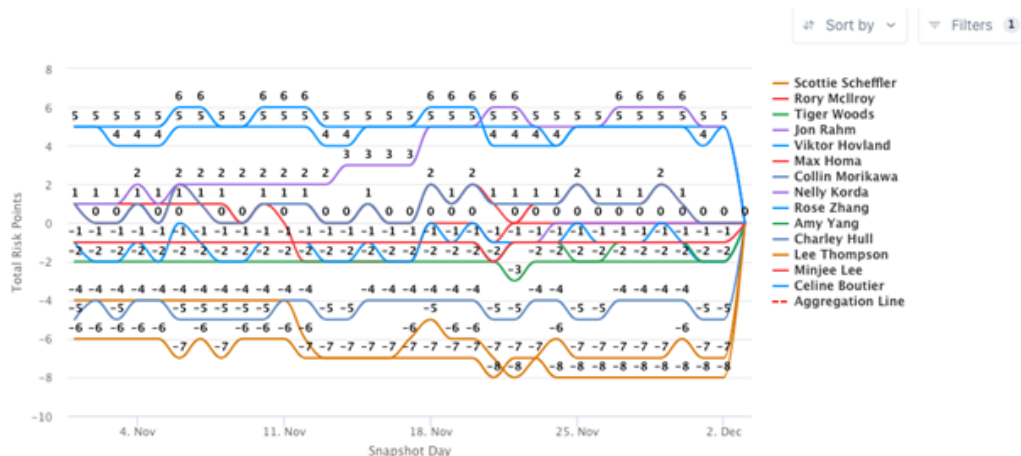


Figure 4: Risk Points and metrics are stored in nightly snapshots for trend analysis

## Learner Risk Metrics

Learner Risk Points leverage a combination of learner engagement, attendance, and progress metrics to assess risk. These metrics are well-grounded in existing educational theories and research (Arizmendi et al., 2022; Kovanović et al., 2015; Whitmer, 2013) and are transparent to instructors, learners, and other stakeholders.

Snapshot Date	Last Name	First Name	Total Risk Points	Course Grade	Course Points	Completed Activities Per Day	Progress Risk	Activity Completion	Points Risk	Progress by Points	Other Engagement Risk
11-30-2024	Morkosa	Collin	0	B	249	0	0%	100%	0	100%	0
11-30-2024	Woods	Tiger	-2	B	380	0	0%	100%	0	100%	-1
11-30-2024	Scheffer	Scottie	-2	B	420	0	0%	100%	0	100%	-4
11-30-2024	Howland	Viktor	5	B	163	0	0%	100%	0	100%	4
11-30-2024	Homa	Max	0	B	235	0	0%	100%	0	100%	0
11-30-2024	Hul	Charley	-3	B	421	0	0%	100%	0	100%	-4
11-30-2024	Yang	Amy	-2	B	323	0	0%	100%	0	100%	-3
11-30-2024	Thompson	Lee	-3	B	410	0	0%	100%	0	100%	-2
11-30-2024	Zhang	Rose	-2	B	341	0	0%	100%	0	100%	0
11-30-2024	Lee	Marge	-1	B	348	0	0%	100%	0	100%	0

Figure 5: Risk Points reports break down sources of risk into different behavioral categories.

- **Engagement** – Includes metrics such as the number of visits, time spent, and participations (e.g., quiz attempts, discussion forum posts). Research consistently shows that engagement is a key predictor of academic success.
- **Attendance** – This is measured by tracking the days since last visit or participation in the LMS and calculating the percentage of days engaged with course materials. A distinction is made between active participation and passive observation.
- **Progress** – Progress is measured using several factors, including course grade, percentage of points earned, and percentage of activities completed. Different progress metrics may be suitable depending on the institutional use of the LMS.

# Transparency and Compliance

All metrics and calculations used in Risk Points are completely transparent to learners, instructors, and other stakeholders, and are compliant with data privacy regulations. This is not a black box system, but one designed to encourage trust among learners, instructors, and other stakeholders. High trust systems have been found to be more effective in supporting educational outcomes (Slade et al., 2019).

- **Granular** - Each metric used in the Risk Points calculation is captured separately and can be reported in detail.
- **Documented** - Each metric is supported by documentation explaining how it is measured and what it represents.
- **Valid** - Definitions of metrics have a clear basis in theory and practice. Dashboards provide tools to validate the appropriateness of each metric based on institutional data.
- **Explainable** - The calculation method is a standard statistical operation (Z-Score) and can be verified from the data.
- **Auditable** - Metrics are captured nightly, and the composition of risk can be reviewed over time via nightly data snapshots.\*
- **Configurable** - Although Risk Points do not require configuration, institutions have the option to disable or exclude any metric in custom calculations.
- **Compliant** - Data retention tools\*\* ensure compliance with privacy regulations, allowing retention limits and individual learner exclusion. Aggregated metrics are captured without exposing private details.

If a metric is not relevant to an institution, e.g. completion criteria have not been assigned for course activities, all learners are assigned a value of 0 and that metric does not contribute to risk points. Snapshots for that metric can be disabled.

Note that snapshots are only captured for active users and courses.

## Metrics Over Time and Trend Analysis

IntelliBoard's Risk Points model also provides the ability to track learner performance over time. By storing daily risk snapshots\*, educators can examine trends in risk metrics, identifying patterns in learner engagement, attendance, and progress that may signal a need for intervention.

Details may easily be filtered by date or by learner, providing both a Daily Risk Snapshot and a Learner Risk History.

For instance, a steady increase in risk points could indicate waning engagement, prompting proactive support from instructors or advisors. Conversely, sudden improvements in these metrics may suggest successful interventions or changes in learner behavior. It can be especially powerful to combine Risk Points with IntelliBoard's InContact communication log tool to look for relationships between intervention communications and changes in risk.

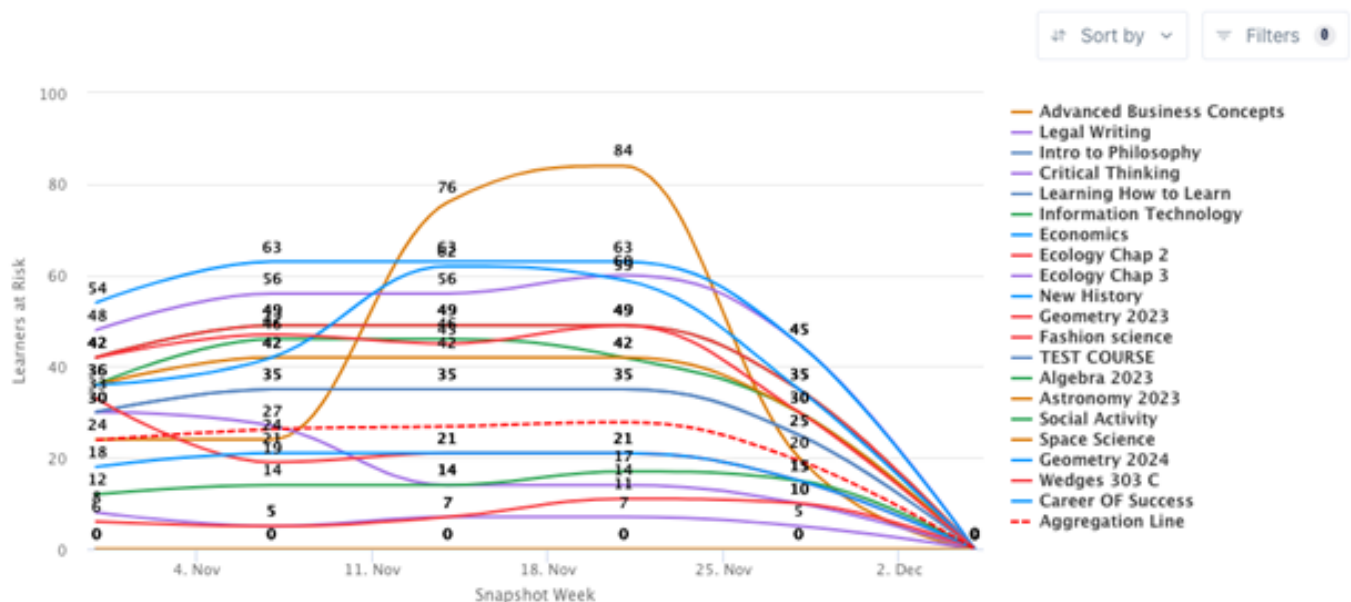


Figure 6: Summary reports allow academic administrators to view risk across multiple courses.



## Use in Notifications

Risk Points serve as a powerful driver for IntelliBoard's Notifications system. Risk Point thresholds can easily drive automated notifications to advisors, instructors, learners, or any other stakeholders. Risk Points can be aggregated by course or by category to alert senior instructors or academic leadership of potential problems before they begin to impact learning and retention. Customizing messages to learners based on their specific behaviors, strengths and weaknesses has been shown to be more effective than generic messages (Pardo et al., 2019).

The screenshot shows the 'Notification Message Body' editor. It includes a rich text editor with various formatting options (bold, italic, underline, link, unlink, list, indent, outdent, undo, redo, text color, background color, link icon). Below the editor is a table titled 'Risk Points Messaging'.

Risk Points	Message
Risk Points > 1	Good initial work. However, try to review the questions you missed. Remember, you can always post questions in the forum.
Risk Points > 0	Good work with the Quiz! You may want to review the answers again in a few days to make sure you fully understand the concepts.
Risk points <= 0	Excellent work with the Quiz! You may want to keep the link handy to review before the final exam.

Figure 7: Messages in notifications can be customized based on risk points.

## Administrative Tools

IntelliBoard provides several tools to administer Risk Points:

- **Data Retention:** Clients can set retention limits and individual learner exclusion. Aggregated metrics are captured without exposing private details.
- **Org Role Permissions:** Administration of data retention and snapshots can be enabled per organizational role.
- **Data Snapshots Service:** Can be enabled or disabled at the client level.
- **Data Processing Log:** Detailed processing logs are provided with client access for troubleshooting or validation.

## Combination with Other Risk Models

The use of statistical measures ensures that risk points are generated consistently across courses and learner cohorts and can subsequently be integrated into either rules or more complex machine learning models for enhanced predictions if desired.

- **Rule-Based** – Data imported from other systems can be processed using rules and combined with standardized Risk Points data.
- **Machine Learning** – Risk Points can be incorporated into Machine Learning models as a way of standardizing inputs across diverse populations of learners and distinct program features, making more powerful and consistent models with less manual configuration.

## Implementation and Future Possibilities

The simplicity of deploying Risk Points makes it an attractive option for educational institutions. By requiring no historical data or manual rule configuration, this tool minimizes the administrative overhead associated with traditional risk assessment models, yet still provides full transparency to the calculations. Additionally, Risk Points can serve as an input to more complex predictive models, enriching machine learning algorithms with standardized, statistically sound metrics. Future developments may include:

- **Course Readiness Evaluations** – Using Risk Points based on course features to assess the readiness of course designs.
- **Instructor Engagement Metrics** – Expanding the system to measure instructor-student interactions.
- **Content Analysis** – Learner usage of different content to identify strongest and weakest resources for learners and potential for course design improvement.
- **Competency Completion** – Applying Risk Points to Competency Learning Plans to evaluate learner progress toward defined goals.

## Conclusion

The Risk Points model presents a novel, no-configuration approach to student risk assessment that simplifies deployment while providing statistically robust insights. As educational institutions continue to evolve in their use of learning analytics, Risk Points offers a valuable intermediate solution that combines ease of use with strong analytical foundations. Through peer comparison and trend analysis, this model helps educators identify at-risk students and take action before issues escalate.

\* Nightly snapshots are enabled per client on request.

\*\* Data retention management tools are in development and expected to release early in 2025.

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