Interactive Visualization Project Report: Student's Cognitive Overload Score (Mental Load Index)

Link of online visualization: [Tableau Public]

1. Problem Definition

University students are specifically at risk of cognitive overload due to academic demands, lifestyle imbalance, and social stressors. Despite growing awareness, students fail to observe burnout's initial signs until academic performance or wellbeing is compromised. As a remedy, this project offers the Mental Load Index (MLI), a composite score derived from sleep hours, study hours, social media usage, and perceived stress. The goal is to allow students to monitor their cognitive load and reflect on how behavioral problems impact academic outcomes. Elevated stress among students has been shown to correlate with diminished academic performance and heightened risk of anxiety and depression (Beiter, Rebecca, et al.) .

This interactive dashboard, developed with Tableau, graphs MLI against determinants of lifestyle and academic performance. The dashboard adheres to Munzner's nested model, following steps from problem domain to interaction design and visual encoding (Munzner et al.)

2. Data and Abstraction

The project works on two datasets: exams.csv (academic grades and demographic data) and Student Mental Stress and Coping Mechanisms.csv (lifestyle and mental health data). Since the datasets don't share a common key, they were joined by index to create an integrated sample. After handling missing values through elimination and normalizing numerical fields (like study hours, sleeping time, use of social media, level of stress), groundwork was initiated to develop a Mental Load Index (MLI). Then, the Mental Load Index (MLI) was created using the following formula:

MLI Score = 0.3 * (Normalized Study Hours)
+ 0.2 * (Normalized Social Media Usage)
+ 0.3 * (1 - Normalized Sleep Duration)
+ 0.2 * (Normalized Stress Level)

The output was then converted to a scale of 0–100 to generate MLI Final, and was categorized as Low, Medium, or High MLI.

Data abstraction focused on:

1. Student demographic variables (gender, race)

2. Behavioral metrics (sleep, study, screen time)
3. Psychological indicators (stress, peer pressure, coping mechanisms)
4. Outcome variable: Academic Performance (GPA)

This formulation aligns with established research showing the combined effects of psychological and behavioral indicators on burnout and school disengagement (Salmela‑Aro et al.).

3. Task Abstraction

The ***high-level analysis*** goals addressed by this visualization are:

- T1: Identify high-risk students for mental overload, helping advisors or students take preventive measures.
- T2: Identify how the mental load is influenced by lifestyle factors (sleep, study habits, and social media).
- T3: Compare the intensity of mental load across demographic groups (e.g., gender) to determine systematic differences.
- T4: Analyze how the interaction of MLI with GPA highlights cognitive overload's influence on outcomes.
- T5: Enable users to reflect on themselves and identify behavioral patterns that contribute to burnout risk.

These top-level objectives were translated into ***low-level interactive tasks***:

- Apply filters on characteristics of students (e.g., gender or GPA) to personalize analysis (T1, T3).
- Utilize the MLI heatmap to rapidly detect high-risk cells through red color signals (T1).
- Read line charts to recognize inverse relationships, for example, more hours of sleep are linked with lower MLI scores (T2).
- Plot scatterplots and jittered plots to examine distribution of MLI by stress levels and social media use (T2, T5).
- Compare GPAs within each MLI category using box plots to investigate performance differences (T4).

These design choices follow task typologies in visual analytics and visualization systems (Brehmer, Munzner et al.)

4. Visual and Interaction Design

Following Munzner's principles:
Encoding:

❖ Red-green color gradients for load in MLI Heatmap

- ❖ Line graphs for time trends (e.g., Study Hours vs. MLI)
- ❖ Box plots for comparing GPA by MLI groupings
- ❖ Bar graphs for showing gendered variations in MLI
- ❖ Scatter plots for Social Media Usage and MLI

Interactions:

- ➢ High-level metrics indicate avg GPA, sleep, MLI, etc.
- ➢ Gender, GPA, and stress level filters
- ➢ Tooltips added for value-specific information
- ➢ The charts are placed on a 3x2 dark background for contrast dashboard grid and uniform color scheme with floating text boxes for the section titles.

All the visual encodings and interaction elements are coupled with specific tasks:

- T1 is facilitated by the red zones in the heatmap, which pick up high-risk students.
- T2 is examined through line plots and scatterplots of lifestyle measures to MLI.
- T3 is addressed using bar plots and gender filter panels.
- T4 is derived based on GPA-disaggregated box plots.
- T5 is unveiled by the KPI measures and tooltip summaries that provoke contemplation.

This design approach reflects persuasive and accessible visual analytics techniques used in personal informatics tools (Günther, David, et al.)

5. Iterative Process

The development process involved multiple iterations, each incorporating user feedback and design refinement:

- ❖ **Version 1:** Version 1 emphasized creating fundamental visuals with raw data and calculating MLI. The interface functioned but was not interactive and poorly organized. Comments indicated labels had to be more legible and grouping improved.
- ❖ **Version 2:**Version 2 introduced parameter filters, color palettes harmonization, and re-designed dashboard sections using layout containers. Initial user feedback showed scatterplot confusion and insufficient context in tooltips. These results highlighted clear legends and direction labels.
- ❖ **Final Version:**Version 3 (Final) included a neater layout, normalized field names, enhanced dark mode font contrast and better tooltips for better readability. A KPI header row for aggregating key measures (GPA, MLI, Sleep, etc.) was added, and standard chart titles were employed throughout.

This iterative approach aligned closely with Munzner's nested model, iterating between data/task abstraction and encoding design to create a system that is both useful and usable (Munzner, et al.).

6. Lessons Learned

This project demonstrated the power of combining behavioral and academic data to reveal hidden stress patterns. Designing for diverse user visualization literacy required simplified labels, minimal clutter, and consistent color-coding. Tooltips and parameter controls significantly enhanced usability. Ranking logic using RANK_UNIQUE allowed dynamic filtering and improved scalability.

It became clear that even visually rich dashboards must remain cognitively accessible, especially when dealing with mental health–related insights. Visual clarity directly impacts user trust and engagement (Few, S et al.)

Acknowledgment:

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Works Cited

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