ISSAQ Theory of Action (ToA) Research Memo 2.0::
Individual Results Support Institutional Understanding, Engagement, and Support

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DIA
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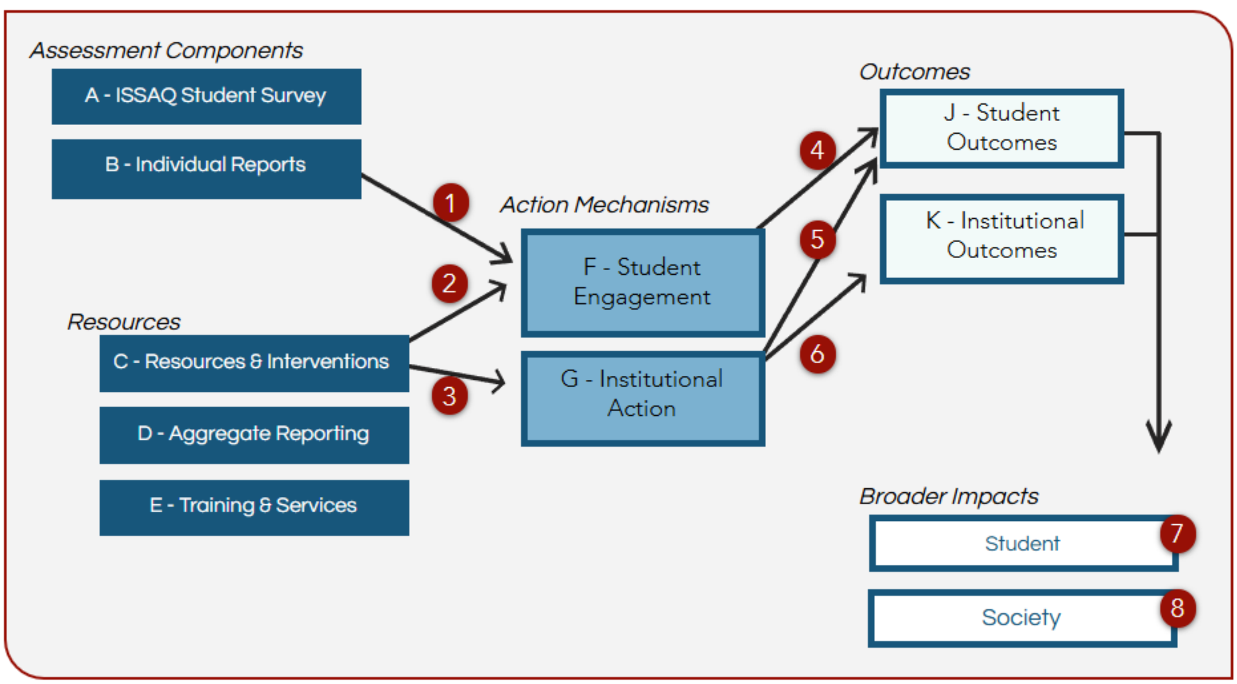
Preface

Theories of action (ToA's) articulate how the components of an assessment model are used and, subsequently, lead to tangible outcomes and impacts (Markle, 2024). Such models are vital for any change-based assessment model (NCME, 2018). Given ISSAQ's focus on improving student success in higher education, a ToA not only helps to demonstrate how assessment results can and should be used, it serves as an agenda for validity research - pinpointing testable claims of measurement, use, and efficacy.

The theory of action outlined here addresses three main aspects of ISSAQ. *Assessment Components* and *Resources* refer to the tools, features, and services provided by DIA Higher Education as part of the platform. *Action mechanisms* refer to the ways in which those features are used across constituencies, primarily focusing on students and those working with them to improve their success (e.g., advisors, coaches, counselors). Finally, *Outcomes* and *Broader Impacts* refer to the changes in behavior and results that one would expect to see across various constituencies (i.e., students, advisors, institutions) and periods of time.



The numbers within the model represent research questions: hypotheses about the connections between the various aspects of this model, how they should be used, and their intended impact. This memo serves as one of a series of studies, reviews, and other resources that will be continually cultivated to ensure the validity of ISSAQ – not just as an assessment – but as a tool to improve student success.

Introduction

Over the past two decades, colleges and universities have increasingly recognized the importance of integrating data into their student success strategies. The emergence of learning analytics and advancement of institutional research infrastructures has allowed for more systematic use of student-level information to identify barriers, tailor interventions, and evaluate outcomes (Siemens & Long, 2011; Kuh et al., 2015). While much of this work has focused on academic and behavioral data—such as course grades, attendance, and LMS activity—there is growing recognition that **noncognitive data** play an equally critical role in understanding and supporting student success.

Noncognitive measures capture the behavioral, motivational, emotional, and social factors that influence how students engage with their learning environments (Sedlacek, 2004; Robbins et al., 2004). These data provide insight into *why* students may struggle or persist, rather than merely *how well* they have performed in the past or at present. Tools such as ISSAQ operationalize these constructs to help institutions identify student strengths and challenges in domains such as self-regulation, motivation, belonging, and persistence. Importantly, the **validity** of such measures in institutional practice extends beyond their psychometric properties to encompass how effectively their results are *used* to inform decisions and drive meaningful improvements in student outcomes (Kane, 2013; Markle, 2024).

To support the hypothesis that ISSAQ data support improved institutional student success strategies, this review synthesizes the literature on three dimensions of noncognitive data use in higher education:

a. improving institutional understanding of student strengths and challenges,

b. supporting analytics-based outreach and advising, and

c. guiding the development and alignment of co-curricular programs and resources.

Enhancing Institutional Understanding of Student Strengths and Challenges

Institutions that gather noncognitive data often find that these results deepen their understanding of students' lived experiences, motivations, and barriers to success. Unlike traditional academic metrics, noncognitive indicators offer a multidimensional view of students that includes affective and behavioral patterns linked to persistence, achievement, and well-being (Farrington et al., 2012; Markle et al., 2013; Richardson, Abrham, & Bond, 2012; Poropat, 2009; Robbins et al., 2004).

Research has consistently shown the value of noncognitive data in predicting student persistence and academic performance above and beyond standardized test scores or prior GPA (Robbins et al., 2004; Komarraju & Nadler, 2013). Such improvement in analytics can help institutions better target outreach and engagement for those students who are unlikely to be successful. Not only is this helpful for guiding interventions to students at risk of attrition, these data can identify previously unquantifiable issues for students who appear academically capable but lack confidence, goal clarity, or social connectedness that support long-term success (Yeager et al., 2019; Thomas, 2012).

Noncognitive data can also provide unique insights to institutions seeking to understand the differential skills, perceptions, and experiences of traditionally underserved populations. For example, studies show that first-generation and underrepresented minority students often report lower belonging and self-efficacy scores, even when academic preparation is equivalent (Museus & Quaye, 2009). Such improvements in understanding groups integrates a psychological perspective into a traditionally sociological view of students (Eaton & Bean, 1995).

This approach aligns with the "validity as use" perspective articulated by Kane (2013), which holds that evidence for validity includes how well data are interpreted and applied in context. When noncognitive results are used to inform institutional understanding, strategy, culture, and practice, they provide a foundation for more equitable and evidence-based student success planning.

Supporting Analytics-Based Outreach and Advising

Using analytics to inform student outreach is one of the most promising applications of noncognitive data. While noncognitive data hold strong predictive efficacy on their own, integration with academic, enrollment, financial, and other data form a robust bank of predictive factors that can help institutions both quantitatively and qualitatively differentiate engagement and support.

Early learning analytics efforts such as Purdue University's *Signals* project demonstrated how predictive models can translate multiple data sources—including engagement indicators and motivational variables—into risk classifications that trigger timely interventions from instructors and advisors (Arnold & Pistilli, 2010). More recent frameworks for "academic analytics" (Campbell et al., 2007; Pistilli et al., 2018) emphasize integrating noncognitive factors into advising systems to move from reactive to *proactive* support. For instance, when students report low self-regulation or academic confidence, advisors can tailor outreach that combines skill coaching with encouragement, rather than standard academic warnings (Simpson & Watson, 2017).

Institutions such as Georgia State University have operationalized this approach at scale through predictive advising systems that incorporate hundreds of risk factors to generate automated alerts and personalized follow-up campaigns (Renick, 2019). These models enable advisors to differentiate between academic and motivational barriers, improving the precision and empathy of institutional outreach.

Evaluations of *Integrated Planning and Advising for Student Success* (iPASS) initiatives showed that colleges implementing integrated analytics and advising platforms achieved earlier identification of struggling students, more frequent advisor-student contact, and greater use of targeted communications (CCRC, 2019). However, researchers emphasize that data use—not just data availability—is the key determinant of impact: analytics are effective only when embedded within advising practices that support meaningful student engagement (Pistilli et al., 2018).

Together, these findings suggest that noncognitive data strengthen the interpretive power of predictive models and the responsiveness of institutional outreach, transforming how colleges deliver personalized support.

Development and Alignment of Co-Curricular Programs

Beyond analytics and advising, noncognitive data also inform how institutions design and align co-curricular supports. Because these constructs capture changeable skills and attitudes, they are directly actionable in program design and evaluation. For example, campuses may use aggregated results to identify cohorts with low time management or help-seeking scores and create workshops, mentoring initiatives, or first-year experience modules to address those needs (Kuh et al., 2010).

The literature on student engagement and institutional effectiveness underscores the value of using noncognitive evidence to shape developmental programming. Tinto (2017) and Kinzie and Kuh (2017) argue that continuous feedback cycles—collecting, interpreting, intervening, and reassessing—are essential for building environments that support student motivation and belonging. Such cyclical models allow institutions to close the loop between assessment and improvement, demonstrating both accountability and growth.

In practice, this might involve linking noncognitive data to campus-wide dashboards that track the outcomes of specific initiatives (e.g., academic coaching, tutoring, or leadership programs) and using subsequent survey administrations to evaluate changes in self-efficacy or belonging. Over time, these feedback loops become powerful sources of validity evidence for tools like ISSAQ, showing that results are meaningfully connected to student learning and institutional change (Kuh et al., 2015).

Importantly, scholars emphasize that successful use of noncognitive data requires organizational alignment and professional development. Advisors, faculty, and student affairs professionals must share a common framework for interpreting the data and acting on it consistently (Kuh et al., 2010; Farrington et al., 2012). When institutions invest in this collective capacity, noncognitive assessment becomes a central component of strategic student success planning rather than a standalone measurement exercise.

Conclusion

The literature offers consistent evidence that noncognitive data have transformative potential when used to enhance institutional understanding, guide analytics-based outreach, and inform co-curricular program design. Across studies, the most effective institutions view these data not as static metrics, but as dynamic inputs for continuous improvement.

By integrating noncognitive insights with academic and behavioral analytics, colleges can develop more holistic, equitable, and student-centered support systems. This process reflects the type of "validity in use" that underpins the effectiveness of ISSAQ: the measure's value lies in its capacity to inform decisions that directly improve student success. As higher education continues to move toward comprehensive, data-informed approaches, ISSAQ provides the conceptual and operational framework to translate noncognitive assessment into actionable institutional change.

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