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Boosting Students’ Engagement with Web-based Assessment Platforms: A Self-determination Theory Perspective

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Abstract:
We examine the connection between technology components, student motivation, and engagement with Web-based assessment platforms. Technology components include feedback, functionality, and response. We built a research model on the motivational technology model as the overarching theory for our investigation. We collected data from 313 undergraduate business students from one Midwestern American institution and analyzed it using CB-SEM. The findings indicate that technology-related factors influence individuals’ motivation (namely, competence and autonomy), which, in turn, impacts engagement. We discuss the results and their implications for research and practice. Additionally, we address the limitations and identify future research opportunities.

Keywords: Engagement, Autonomy, Self-determination, Web-based Assessment, Functionality

Fiona Nah was the accepting senior editor for this paper.
1 Introduction

The digital era we live in has directly affected almost every industry, including the education sector (Merhi, 2015; Ahluwalia & Merhi, 2020). This change has had a direct impact on how instructors teach and assess students and how students learn. Several institutions have invested in tools to make the learning process more efficient and effective (Al-Emran et al., 2016; Beard et al., 2019; Simonson et al., 2019). Paper textbooks have given way to digital books, the physical classroom has evolved into a virtual classroom, and paper-based assessments have moved from the classroom to the Web. Studies conducted globally have documented the massive growth in e-book use and the impact that e-books and distance delivery have had on student learning (Almarashdeh, 2016; Horner, 2017; Lin et al., 2019). As online technologies have proliferated, so too have web-based assessment platforms in recent years. Indeed, educators also increasingly used such platforms due to the recent coronavirus disease of 2019 (COVID-19) pandemic, where many in-person classes had to convert to online. Nevertheless, we lack research on Web-based assessment platforms, especially platforms that publishers such as McGraw-Hill Connect, Cengage Brain, and Pearson’s MyLab have designed, with respect to their impact on students.

Reports suggest that institutions and individual instructors have increasingly adopted publisher-designed assessment platforms to assess their students (e.g., Molnar, 2017). Institutions, including the one where we conducted this study, have received discounts for adopting these platforms. Students save money, while institutions do not have to worry about technical issues and maintenance. The COVID-19 pandemic has also forced faculty and institutions to seek technologies that help them transition from face-to-face courses to hybrid or online modalities. Simultaneously, students’ engagement has always been a major concern for instructors. Previous studies have explored the complex aspects of students’ engagement in digital learning environments (e.g., Delaney et al., 2019). Despite much research on students’ experiences with different technologies, we identify a gap in existing literature related to work that has analyzed student engagement using Web-based assessment platforms. To our knowledge, no study has demonstrated the role that technological factors play in individuals’ motivation and engagement. Thus, in this study, we analyze factors that affect students’ engagement with Web-based assessment platforms and, thus, contribute to the body of knowledge on this topic. This study addresses two research questions:

**RQ1:** How engaged are students with Web-based assessment platforms?

**RQ2:** What impacts their engagement?

Scholars, in general, have stressed the role of engagement. In education, student engagement has a significant impact on both academic outcomes and the overall learning process. Kuh et al. (2007) highlighted the crucial role that student engagement plays in determining learning outcomes. Reeve (2013) stressed the important role that students’ active engagement plays in creating their learning environments. Zydney et al. (2022) explored online engagement in the digital landscape context and noted that researchers must go beyond course-level indicators to fully understand online engagement. Similarly, scholars (e.g., Dutta & Mishra, 2021) in the information systems (IS) discipline have examined the factors that impact users’ engagement with technologies (e.g., AI-based virtual assistants) since they ensure effectiveness and success. Engagement is a precedent to adoption, increases productivity, develops new skills, aids in change management, and fosters collaboration (Choudhary et al., 2022; Wang et al., 2021). Thus, we need to examine the factors that impact engagement.

In this study, we explicitly focus on examining how technology-related factors and students’ self-perceived thoughts and feelings affect their engagement with Web-based assessment platforms. We explore the role of motivational factors in the relationship between technological factors and engagement. The motivational technology model (MTM) posits that a technology’s technological features can trigger a person’s motivational and psychological needs for competence, autonomy, and relatedness (Sundar et al., 2012). The MTM model depicts the relationship between technological factors, self-determination factors, and engagement. It argues that self-determination theory’s (SDT) motivational factors—autonomy, competence, and relatedness—mediate the relationship between technological factors and engagement. Researchers originally proposed the MTM in the digital health context and have not yet empirically assessed it.

We identified three common technical factors that publishers use in their marketing campaigns to increase our findings’ generalizability. Publishers argue that their Web-based platforms offer students constructive feedback, high functionality, and fast response. They also argue that students and instructors perceive these technical factors as important. For this reason, we chose these three factors as the technological factors. We also examine two factors from SDT—autonomy and competence—as motivational factors. The third
SDT component, relatedness, refers to connectedness among peers and the interactions among them. Since we explore the interaction between students and Web-based platforms, we did not incorporate relatedness as a factor in the research model because it falls outside our scope here.

With this study, we add to the body of knowledge by assessing the MTM and the influence of crucial factors on students’ engagement with Web-based assessments that publishers provide using data from a relatively large sample size (313 students). This study also contributes to the body of literature on individuals’ engagement with IS in general. Although we conducted this study in a Web-based platform context, the results can be generalized to other contexts. Our findings may also assist practitioners. For instance, it can help developers, instructional designers, programmers, and e-learning/IT publishers by assessing the role of three crucial technological factors feedback, functionality, and response.

This paper proceeds as follows: in Section 2, we review the literature on Web-based assessment platforms and engagement. In Section 3, we discuss the theoretical framework that we used to build the research model before discussing our hypotheses in Section 4. In Section 5, we explain the methodology we followed. In Section 6, we discuss how we analyzed the data and present the results. In Section 7, we discuss our findings’ implications for research and practice, possible future research avenues, and limitations. Finally, in Section 8, we conclude the paper.

2 Literature Review

2.1 Web-Based Assessment Platforms

A Web-based assessment platform allows educators to design, schedule, administer, and report on class requirements, such as assignments, quizzes, and exams. Such platforms replace the traditional paper-based testing methods that educators have used throughout history. These platforms offer convenience, accessibility, simplicity, and efficiency (Cigdem et al., 2016; Matthews et al., 2019; Williams & Williams, 2010). Students can access assessments at any time and place from any device. Thus, they no longer need to travel to a specific location to take a quiz or an exam. Furthermore, the increased efficiency that these platforms provide saves teachers time by making it possible for them to concentrate on expanding the content they cover and/or cover important topics in greater depth (Merhi & Meisami, 2022, 2023; Panigrahi et al., 2020).

To enhance students’ learning experience, publishers design Web-based assessment platforms with extensive functionalities that cater to various learning preferences and styles, with interactive elements and tailored feedback systems. They also offer prompt, targeted, and useful feedback that helps students gain mastery and comprehension. In sum, these systems can enhance learning via integrating feedback, helping instructors provide timely responses, and various functionalities in an online learning environment which leads to a more effective and engaged educational experience.

2.2 Engagement

Engagement refers to an individual’s active involvement in a learning task (Reeve et al., 2004). It reflects an individual’s enthusiastic participation in a task and subsumes many interrelated motivation expressions, such as intrinsically motivated behavior, self-determined extrinsic motivation, work orientation, and mastery motivation (Reeve et al., 2002).

In educational research, student engagement exerts a substantial influence on both academic results and the broader learning process. Bowen (2005) highlighted engagement’s growing importance as a differentiating factor in effective educational practices for students. Kuh et al. (2007) underscore the critical role that student engagement plays in shaping learning outcomes. According to Freeman et al. (2014), engaged learning approaches encourage critical thinking and more thorough material comprehension. Johnson and Johnson (1999) showed that encouraging students to engage fully in class discussions and activities helps them feel more in control of their education and develops a collaborative learning environment, which improves students’ learning.

Researchers have also examined users/students’ engagement with different technologies. Chen et al. (2010) explored the impact of Web-based learning technologies on student engagement and self-reported learning outcomes in both traditional in-person and virtual learning environments. Using items from the National Survey of Student Engagement (NSSE), they found that using learning technology had a positive associated with student engagement and learning outcomes. They also discovered that students who
employed the Internet and the Web for educational purposes exhibited higher scores on traditional engagement metrics, were inclined to employ deep learning strategies, and reported greater advancements in general education, practical competence, and social and personal development.

Reeve (2013) stressed the importance of students’ active engagement as it helps them gain better control over their own learning. Rodriguez-Lluesma et al. (2021) delved into the impacts of digital platforms and emphasized their crucial role in fostering engagement among Generation Z students. Zydney et al. (2022) explored online engagement in the digital landscape and realized that researchers must go beyond course-level indicators to fully understand online engagement.

Bergdahl et al. (2018) underscored the opportunities and challenges associated with using learning technologies. They argued that applying these technologies in a mismanaged manner may obscure the learning process and diminish student engagement. However, adept orchestration can foster diverse interactions and effectively engage each student. Their study highlights how, by using learning technologies judiciously, educators can optimize both student engagement and learning outcomes. The authors also urged researchers to investigate student engagement through learning technologies, improve design implications, and advocate for teaching practices that create opportunities for all students to actively participate in learning activities.

Based on this brief literature review, one can see that researchers have examined the impact that engagement with different technologies has on students’ performances and learning outcomes. Extant studies have also examined the impact of technology on students’ engagement and argued that technology may be a barrier to students’ engagement. However, the extant literature has not investigated students’ engagement with Web-based assessment platforms or what impacts engagement.

3 Theoretical Framework

We built this paper’s research model on the motivational technology model (MTM) (Sundar et al., 2012). The MTM analyzes the complex interaction between technology characteristics and user motivation. The model highlights critical components such as customization, navigability, and interaction and explains how these aspects closely support user engagement and intrinsic motivation. The MTM argues that SDT motivational factors—themselves impacted by technological factors—influence the extent to which users engage with IS and, furthermore. In other words, SDT factors serve as a mediator between technological factors and engagement. We should note that researchers have not yet empirically assessed the MTM, which constitutes one contribution that we make with this paper.

Researchers have extensively researched SDT, a macro-theory of human motivation (Ryan & Deci, 2000). We chose this theory because it suggests that its factors increase an individual’s intrinsic motivation, which, in turn, may improve engagement. Among its basic components include extrinsic and intrinsic motivation; it also entails a set of basic psychological conditions that underpin motivation (Gagné & Deci, 2005). Extrinsic motivation “refers to doing something because it leads to a separable outcome” (Ryan & Deci, 2000, p.55). Roca and Gagné (2008) suggested that three basic psychological needs dictate a person’s intrinsic motivation: the need for relatedness, the need for competence, and the need for autonomy. Relatedness refers to the notion that one feels connected to other people, competence refers to the feeling that one has achieved valued results, and autonomy connotes the psyche’s desire to take responsibility for itself, self-regulate, and self-initiate (Ryan & Deci, 2017).

In the IS education literature, researchers have examined these three concepts and found them to influence whether students adopt and continue to use e-learning technologies (Nikou & Economides, 2017; Sørebo et al., 2009). However, we do not know what intermediate role the SDT factors have in determining students’ engagement with the technology or their learning environment. Prior studies show that SDT factors act at the intermediary level between mobile evaluation and technology adoption (Nikou & Economides, 2017). In this study, we assess not only the direct impact that competence and autonomy but also the impact that their antecedents—feedback, functionality, and response—have on students’ engagement. Because connectedness and interaction among peers define relatedness, as we mentioned above, we believe its application lacks relevance to this study. Thus, we dropped the concept from our proposed model.

4 Research Model and Hypotheses

Figure 1 depicts our research model. The model asserts that students’ engagement is a function of their self-perceived competence and autonomy, which other factors (namely, feedback, functionality, and
response) influence. We empirically examine the MTM and extend the SDT’s traditional factors by assessing their intermediary roles between technological factors and engagement. The MTM (Sundar et al., 2012, p. 115) asserts that high levels of technological factors such as navigability, interactivity, and customization lead to higher levels of intrinsic motivation. At the same time, higher levels of intrinsic motivation lead to greater engagement with technology. In this paper, we identified the most crucial technological factors for Web-based assessment platforms as feedback, functionality, and response. Thus, we focus on the indirect role that feedback, functionality, and response play in impacting engagement through technological factors. Since we follow the MTM as a guide, we do not assess the relationships between the technological factors and feedback. We discuss the hypotheses in the following paragraphs.

![Research Model](image)

**Figure 1. Research Model**

### 4.1 Perceived Competence and Engagement

According to the SDT, competence refers to the yearning to feel productive in accomplishing one’s desired goals (Ryan & Deci, 2000). Marcolin et al. (2000) define competence as users’ capability to use technology to the maximum degree conceivable to optimize their job-related performance. Basselier et al. (2001), based on analyzing the literature, found that competence combines knowledge, skills, and individual personality traits. Accordingly, we deduce that perceived competence refers to the ability to consistently apply the knowledge and skills one has acquired to accomplish a given task on a Web-based assessment platform.

Orazbayeva et al. (2020) analyzed academic engagement in education-driven university-business cooperation and focused primarily on relatedness, autonomy, and competence. They found that autonomy and competence significantly influenced engagement in course-related activities. Generally speaking, motivation and engagement relate to each other because motivation leads to continuous learning and increases engagement (Liu et al., 2022; Merhi, 2019). We argue that, to engage in the learning process and enjoy using a Web-based assessment platform, students must have and apply their skills and knowledge. The higher their competence in using the Web-based assessment platform, the more persistent and engaged students become. Thus, we can reasonably expect that students with greater competence in using Web-based assessment platforms will become more engaged more in the activities and the learning process. Accordingly, we postulate that competence in using Web-based assessment platforms positively impacts engagement. Thus, we hypothesize that:

**H1**: Perceived competence in using Web-based assessment platforms positively impacts engagement with the learning content on the platforms.

### 4.1.1 Perceived Autonomy and Engagement

SDT posits that individuals who perceive themselves as having high autonomy concerning an activity lead to improved intrinsic and extrinsic motivation (Ryan & Deci, 2000). As the literature has defined it, autonomy refers to an individual’s deliberate acts that maximize the individual’s knowledge in a learning environment. Standage et al. (2006) found that learning activities that appear to support autonomy lead to higher intrinsic motivation. Sørebe et al. (2009) noted that perceived autonomy positively affects intrinsic motivation.
Flexibility and convenience, two Web-based assessment characteristics, increase the extent to which people perceive that they have autonomy in using these platforms. Students who perceive themselves as having high autonomy in using Web-based assessment platforms know how to choose the activities that lead them to excel in a learning environment (Reeve et al., 2004). As we mention above, since motivation (in this case autonomy) and engagement relate to each other (Liu et al., 2022), one can expect individuals with high levels of autonomy in using Web-based assessment platforms to have high levels of concentration and emotional quality, which leads them to higher engagement levels. Furthermore, we note again that Orazbayeva et al. (2020) found that autonomy and competence significantly influenced engagement in course-related activities. In this study, we argue that a higher level of autonomy in using Web-based assessment platforms increases the level of engagement with these platforms. Thus, we hypothesize that:

H2: Perceived autonomy in using Web-based assessment platforms positively impacts engagement with the learning content on the platforms.

4.1.2 Perceived Feedback and Competence

Feedback represents a major information source that helps students to correct misconceptions, recreate and validate knowledge, improve academic achievement, and enhance motivation (Wang & Wu, 2008). Nicol (2009, p. 337) emphasized that “Feedback should be of sufficient quantity; timely; it should focus on learning not marks; it should be related to assessment criteria and be understandable, attended to and actually used by students to make improvements on their work” Researchers have found that feedback impacts self-esteem and self-efficacy (Pintrich & Schunk, 2002). We argue that evaluative feedback on Web-based assessment platforms, which directly identifies whether a student completed a task correctly, will significantly affect students’ competence in using the platforms. As for why, students can improve their performance based on the feedback they get from the Web-based assessment platforms and become motivated to complete their assigned tasks efficiently. If students perceive a platform’s feedback as intuitive and easy to understand, they will be more likely to feel competent in using the system. Based on this reasoning, we argue that steady and reliable feedback from a web-based assessment platform gives students a sense of control and helps them improve their skills. Thus, we hypothesize that:

H3a: Feedback received from using Web-based assessment platforms positively impacts perceived competence in using the platforms.

Perceived Feedback and Autonomy

The existing literature has chiefly focused on the impact of positive feedback on individuals’ motivation. According to Krenn et al. (2013) and Mumm and Mutlu (2011), positive feedback can motivate individuals to set better quality goals for their tasks and, thus, increase their performance. Positive feedback can satisfy a recipient’s sense of autonomy as opposed to negative feedback. Positive feedback facilitates learners’ ability to complete a learning task as fast, if not faster, and with greater accuracy than negative feedback (Barrow et al., 2008). Thus, positive feedback from Web-based assessment platforms can increase feelings of competence and autonomy in using these platforms. Giving timely feedback to students enables them to better plan what subject to study next and what tool to use to accomplish their goals in the highly autonomous environment that a Web-based assessment platform provides. We hypothesize that Web-based assessment platforms that provide thought-provoking feedback, feedback that people perceive as useful and fair, and feedback that focuses on key learning objectives will have a positive impact on their autonomy in using these platforms. Thus, we hypothesize that:

H3b: Feedback received from using Web-based assessment platforms positively impacts perceived autonomy in using the platforms.

4.1.3 Perceived Functionality and Competence

Perceived functionality refers to the extent to which users evaluate a system, its features, and its organizational tools as effective and flexible. IS scholars have examined the influence of functionality on performance expectations (Wu et al., 2010), but no study has examined the impact of functionality on competence. According to MTM, “optimal levels of navigability, interactivity, and customization will lead to higher levels of Intrinsic Motivation” (Sundar et al., 2012, p. 115). Using the same logic, we argue that the Web-based assessment platform’s functionality, as a technological factor, affects how students perceive their competence in using these platforms. Systems with a user-friendly interface and logical interactions contribute to users’ confidence in their ability to use these systems. We contend that Web-based assessment platforms with higher functionality levels lead to higher levels of competence in using them.
because well-designed platforms motivate students and allow for easier learning and, thus, improve students’ performance in given assignments. Web-based assessment platforms continue to develop and have enabled students to participate in the learning process anywhere, anytime, and on their own schedule. Furthermore, the many tools available on these platforms have enabled students to use the teaching methods, technologies, and pedagogical tools that best meet their needs and motivate them to perform better. Nevertheless, students are unlikely to accomplish their desired tasks without a high-functional learning platform. Thus, we hypothesize that:

\textbf{H4a:} Functionality of Web-based assessment platforms positively impacts perceived competence in using the platforms.

4.1.4 Perceived Functionality and Autonomy

Lewis et al. (2014) investigated the benefits and challenges of online learning for students at risk of dropping out of high school. They found that students found it challenging to be responsible for their own learning and manage their time even though they appreciated the opportunity to work ahead and study at their own pace. The authors argued that online learning environments can help at-risk students overcome challenges and find success with proper support structures in place. Further, Sørebø et al. (2009) examined how students perceived YouTube and its impact on autonomous online learning and found that 141 undergraduate students experienced more autonomy when searching for supporting material on YouTube in terms of initiative, responsibility, self-confidence, and decision making. Furthermore, they found a good Internet connection to be essential to engaging with YouTube. We postulate that a Web-based assessment platform’s perceived functionality has a positive impact on students’ perceived autonomy in using these platforms. Web-based assessment platforms provide useful and versatile tools and features that adapt to the way in which each student learns best. In turn, students gain more control over the way they use the platform that best fits them. As a result, students feel more autonomous when they use a Web-based assessment platform. Thus, we hypothesize that:

\textbf{H4b:} Functionality of Web-based assessment platforms positively impacts perceived autonomy in using the platforms.

4.1.5 Perceived Response and Competence

How people respond to a system often relates to how fast a system responds and its consistency. We argue that swift and responsive systems contribute to users’ sense of competence. A system that responds promptly to user inputs creates a seamless and efficient experience and leads users to feel more capable and in control. When users experience a system that responds promptly to their commands, they develop a sense of capability (Diederich et al., 2021). They feel that their actions have a direct and immediate impact, and they can navigate the system with ease (Islam, 2012). In our case, we argue that the faster the response a student receives from the Web-based assessment platform, the more motivated students become, which leads them to believe they can competently use these systems. Thus, we hypothesize that:

\textbf{H5a:} Responses from Web-based assessment platforms positively impact perceived competence in using the platforms.

4.1.6 Perceived Response and Autonomy

In a qualitative study, Baru et al. (2020) explored whether e-media promotes autonomy and found positive results. In particular, they found that students showed enthusiasm when using e-media and mentioned positive feedback that triggered them to be autonomous. We assert that Web-based assessment platforms that respond in a fast, consistent, and reasonable manner contribute to students’ perception of autonomy in using them. In other words, students can study more effectively when they receive more timely, complete, and meaningful responses. This results in students feeling more autonomous when using the platform. Two characteristics can be associated with a good response: time and quality of response. Thus, we hypothesize that:

\textbf{H5b:} Responses from Web-based assessment platforms positively impact perceived autonomy in using the platforms.

In our study, we used the following control variables: gender, major, GPA, hours of study, and course grade.
5 Research Method, Data Collection, and Measurement

We used the survey methodology to assess our proposed hypotheses and research model. We asked students from one public university's College of Business in the Midwest of the United States to take part in this study. Junior and senior students in management information systems (MIS), finance, and marketing courses participated in the study. We asked 345 students in total to complete the paper-based survey. Of the 345 surveys, we could not use 32 due to incompletion. Our final analysis included 313 valid responses. As a result, the effective response rate was about 91 percent. In total, our survey participants comprised 53.04 percent males and 46.96 percent females. Furthermore, 75 percent were aged 21 to 25. In terms of computer skills, most students (about 78%) had intermediate computer skills. We also note that participants did not receive any incentives for participating in this study—students participated completely optionally. Table 1 shows the respondents’ demographic characteristics.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>166</td>
<td>53.04</td>
</tr>
<tr>
<td>Female</td>
<td>147</td>
<td>46.96</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-20</td>
<td>10</td>
<td>3.19</td>
</tr>
<tr>
<td>21-25</td>
<td>236</td>
<td>75.40</td>
</tr>
<tr>
<td>26-30</td>
<td>49</td>
<td>15.65</td>
</tr>
<tr>
<td>31-35</td>
<td>14</td>
<td>4.47</td>
</tr>
<tr>
<td>&gt;35</td>
<td>4</td>
<td>1.28</td>
</tr>
<tr>
<td>Computer Skills</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginner</td>
<td>15</td>
<td>4.79</td>
</tr>
<tr>
<td>Intermediate</td>
<td>243</td>
<td>77.64</td>
</tr>
<tr>
<td>Expert</td>
<td>55</td>
<td>17.57</td>
</tr>
</tbody>
</table>

We adopted the scale items from prior literature and adjusted them to the Web-based assessment platform context. We adopted the scale items for system response and system functionality from Pituch and Lee (2006). We adopted the autonomy and competence scale items from Sørebø et al. (2009). We adopted engagement measures from Webster and Ahuja (2006). We developed the feedback measures ourselves based on Lizzio and Wilson (2008). All items ranged from "strongly disagree" to "strongly agree" using a five-point Likert scale, and we modeled the constructs as reflective. Appendix A contains the measures that we used in this study.

6 Data Analysis and Results

Before employing statistical procedures on the data, we had to identify data anomalies such as missing data and outliers. We checked the data for statistical assumption violations and did not find any. Further, the test for outliers showed no evidence that we needed to make any corrective treatments. We also examined the data for normality and linearity assumptions and did not find any anomalies. In Table 2, we show the detailed statistics for each construct that we used in the study. As the table shows, students responded favorably to engagement with the platform, and all means exceeded 3 out of 5 on the scale.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>Std. deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomy</td>
<td>3.574</td>
<td>0.960</td>
</tr>
<tr>
<td>Competence</td>
<td>4.003</td>
<td>0.786</td>
</tr>
<tr>
<td>Engagement</td>
<td>3.181</td>
<td>1.148</td>
</tr>
<tr>
<td>Feedback</td>
<td>3.577</td>
<td>0.902</td>
</tr>
<tr>
<td>Functionality</td>
<td>3.969</td>
<td>0.784</td>
</tr>
<tr>
<td>Response</td>
<td>3.885</td>
<td>0.785</td>
</tr>
</tbody>
</table>

6.1 Measurement Model Assessment

We assessed the items' psychometric properties using Smart-PLS. We analyzed the results' reliability based on composite reliabilities and Cronbach’s alpha. Cronbach’s alpha coefficients ranged from 0.79 to 0.92,
and all items’ reliability coefficients exceeded 0.87, which indicates that the items were reliable measures for their respective constructs (Chin, 1998; Vinzi et al., 2010). Additionally, all constructs had AVEs above the 0.5 threshold, which indicates sufficient convergent validity (Hair et al., 2010). In addition, the outcomes denote that the items employed in this research possessed high convergent validity as they loaded highly on their respective factors. Table 3 shows these results.

Table 3. Measurement Quality Indicators

<table>
<thead>
<tr>
<th>Latent construct</th>
<th>Item</th>
<th>Loading</th>
<th>t Value</th>
<th>Cronbach’s alpha</th>
<th>Composite reliability</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedback</td>
<td>Feedback1</td>
<td>0.882</td>
<td>55.906</td>
<td>0.896</td>
<td>0.928</td>
<td>0.762</td>
</tr>
<tr>
<td></td>
<td>Feedback2</td>
<td>0.905</td>
<td>67.058</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Feedback3</td>
<td>0.851</td>
<td>37.112</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Feedback4</td>
<td>0.854</td>
<td>46.588</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Autonomy</td>
<td>Autonomy1</td>
<td>0.872</td>
<td>54.451</td>
<td>0.877</td>
<td>0.924</td>
<td>0.803</td>
</tr>
<tr>
<td></td>
<td>Autonomy2</td>
<td>0.912</td>
<td>56.344</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Autonomy3</td>
<td>0.905</td>
<td>67.874</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>Competence1</td>
<td>0.872</td>
<td>40.210</td>
<td>0.851</td>
<td>0.924</td>
<td>0.770</td>
</tr>
<tr>
<td></td>
<td>Competence2</td>
<td>0.850</td>
<td>32.211</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Competence3</td>
<td>0.910</td>
<td>76.928</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>Engagement1</td>
<td>0.928</td>
<td>89.523</td>
<td>0.915</td>
<td>0.946</td>
<td>0.855</td>
</tr>
<tr>
<td></td>
<td>Engagement2</td>
<td>0.931</td>
<td>78.949</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Engagement3</td>
<td>0.914</td>
<td>77.379</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Response</td>
<td>Response1</td>
<td>0.887</td>
<td>62.258</td>
<td>0.896</td>
<td>0.936</td>
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<tr>
<td></td>
<td>Response2</td>
<td>0.922</td>
<td>70.078</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Response3</td>
<td>0.921</td>
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<td></td>
</tr>
<tr>
<td>Functionality</td>
<td>Functionality1</td>
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<td>0.793</td>
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<td>0.717</td>
</tr>
<tr>
<td></td>
<td>Functionality2</td>
<td>0.746</td>
<td>18.056</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Functionality3</td>
<td>0.804</td>
<td>29.084</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Functionality4</td>
<td>0.813</td>
<td>36.420</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4 includes all the measures’ cross-loadings. The results also indicate that the items measured the relevant constructs and only those constructs.
### Table 4. Cross-Loadings

<table>
<thead>
<tr>
<th></th>
<th>Autonomy</th>
<th>Competence</th>
<th>Engagement</th>
<th>Feedback</th>
<th>Functionality</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedback1</td>
<td>0.516</td>
<td>0.436</td>
<td>0.539</td>
<td>0.882</td>
<td>0.540</td>
<td>0.523</td>
</tr>
<tr>
<td>Feedback2</td>
<td>0.436</td>
<td>0.460</td>
<td>0.525</td>
<td>0.905</td>
<td>0.501</td>
<td>0.520</td>
</tr>
<tr>
<td>Feedback3</td>
<td>0.424</td>
<td>0.439</td>
<td>0.530</td>
<td>0.851</td>
<td>0.458</td>
<td>0.440</td>
</tr>
<tr>
<td>Feedback4</td>
<td>0.475</td>
<td>0.431</td>
<td>0.524</td>
<td>0.854</td>
<td>0.530</td>
<td>0.450</td>
</tr>
<tr>
<td>Autonomy1</td>
<td>0.872</td>
<td>0.480</td>
<td>0.478</td>
<td>0.462</td>
<td>0.507</td>
<td>0.403</td>
</tr>
<tr>
<td>Autonomy2</td>
<td>0.912</td>
<td>0.481</td>
<td>0.431</td>
<td>0.465</td>
<td>0.524</td>
<td>0.482</td>
</tr>
<tr>
<td>Autonomy3</td>
<td>0.905</td>
<td>0.521</td>
<td>0.468</td>
<td>0.501</td>
<td>0.528</td>
<td>0.451</td>
</tr>
<tr>
<td>Competence1</td>
<td>0.512</td>
<td>0.872</td>
<td>0.481</td>
<td>0.452</td>
<td>0.572</td>
<td>0.462</td>
</tr>
<tr>
<td>Competence2</td>
<td>0.441</td>
<td>0.850</td>
<td>0.312</td>
<td>0.389</td>
<td>0.514</td>
<td>0.476</td>
</tr>
<tr>
<td>Competence3</td>
<td>0.493</td>
<td>0.910</td>
<td>0.480</td>
<td>0.480</td>
<td>0.573</td>
<td>0.412</td>
</tr>
<tr>
<td>Engagement1</td>
<td>0.500</td>
<td>0.436</td>
<td>0.928</td>
<td>0.610</td>
<td>0.461</td>
<td>0.328</td>
</tr>
<tr>
<td>Engagement2</td>
<td>0.443</td>
<td>0.441</td>
<td>0.931</td>
<td>0.601</td>
<td>0.436</td>
<td>0.339</td>
</tr>
<tr>
<td>Engagement3</td>
<td>0.476</td>
<td>0.488</td>
<td>0.914</td>
<td>0.552</td>
<td>0.475</td>
<td>0.351</td>
</tr>
<tr>
<td>Response1</td>
<td>0.451</td>
<td>0.467</td>
<td>0.352</td>
<td>0.507</td>
<td>0.514</td>
<td>0.887</td>
</tr>
<tr>
<td>Response2</td>
<td>0.441</td>
<td>0.493</td>
<td>0.322</td>
<td>0.504</td>
<td>0.531</td>
<td>0.922</td>
</tr>
<tr>
<td>Response3</td>
<td>0.465</td>
<td>0.433</td>
<td>0.330</td>
<td>0.504</td>
<td>0.564</td>
<td>0.921</td>
</tr>
<tr>
<td>Functionality1</td>
<td>0.520</td>
<td>0.500</td>
<td>0.366</td>
<td>0.436</td>
<td>0.778</td>
<td>0.492</td>
</tr>
<tr>
<td>Functionality2</td>
<td>0.465</td>
<td>0.418</td>
<td>0.382</td>
<td>0.440</td>
<td>0.746</td>
<td>0.464</td>
</tr>
<tr>
<td>Functionality3</td>
<td>0.352</td>
<td>0.518</td>
<td>0.310</td>
<td>0.399</td>
<td>0.804</td>
<td>0.426</td>
</tr>
<tr>
<td>Functionality4</td>
<td>0.472</td>
<td>0.545</td>
<td>0.479</td>
<td>0.540</td>
<td>0.813</td>
<td>0.466</td>
</tr>
</tbody>
</table>

When comparing the square root of the AVE with each construct’s correlation coefficients, one can see that each construct relates more closely to its own construct than the others. All correlation coefficients fell below than the square root of the AVE values, which indicates discriminant validity. Table 5 shows the results.

### Table 5. Fornell-Larcker Criterion

<table>
<thead>
<tr>
<th></th>
<th>Autonomy</th>
<th>Competence</th>
<th>Engagement</th>
<th>Feedback</th>
<th>Functionality</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomy</td>
<td>0.896</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>0.552</td>
<td>0.877</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>0.512</td>
<td>0.492</td>
<td>0.925</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feedback</td>
<td>0.532</td>
<td>0.506</td>
<td>0.535</td>
<td>0.873</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Functionality</td>
<td>0.580</td>
<td>0.532</td>
<td>0.495</td>
<td>0.583</td>
<td>0.847</td>
<td></td>
</tr>
<tr>
<td>Response</td>
<td>0.497</td>
<td>0.509</td>
<td>0.368</td>
<td>0.554</td>
<td>0.590</td>
<td>0.910</td>
</tr>
</tbody>
</table>

Diagonal values represent the square roots of the AVE. Off-diagonal elements represent the correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

Table 6 presents the results of the Heterotrait-Monotrait ratio of correlations (HTMT). All HTMT values fell below the 0.90 threshold, which indicates discriminant validity between all measured constructs (Henseler et al., 2015; Ringle et al., 2022). Hence, the items used in this study demonstrated adequate psychometric properties.
### 6.2 Structural Model Assessment and Hypotheses Testing

We used CB-SEM with SmartPLS 4 to evaluate the relationships between the latent constructs. Figure 2 displays the analysis results graphically. It shows the path coefficients and their significance levels. It also presents the variance ($R^2$) of the three constructs: competence, autonomy, and engagement.

![Figure 2. Results](image)

#### Table 6. HTMT Results

<table>
<thead>
<tr>
<th></th>
<th>Autonomy</th>
<th>Competence</th>
<th>Engagement</th>
<th>Feedback</th>
<th>Functionality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Competence</td>
<td>0.537</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>0.573</td>
<td>0.452</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feedback</td>
<td>0.600</td>
<td>0.577</td>
<td>0.503</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Functionality</td>
<td>0.596</td>
<td>0.566</td>
<td>0.497</td>
<td>0.588</td>
<td></td>
</tr>
<tr>
<td>Response</td>
<td>0.460</td>
<td>0.489</td>
<td>0.398</td>
<td>0.582</td>
<td>0.499</td>
</tr>
</tbody>
</table>

**Note:** ***: Significant at 0.001 level; **: Significant at 0.01 level; *: Significant at 0.05 level

The data supported all our hypotheses, though they exhibited significance at different statistical levels. We identified GPA as the only control variable that had a significant impact on students’ engagement with Web-based assessment platforms. Table 7 presents the values of the model fit indices.

#### Table 7. Results of Model-Fit Indices

<table>
<thead>
<tr>
<th>Fit Index</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square</td>
<td>396.567</td>
</tr>
<tr>
<td>Chi sqr/df</td>
<td>2.494</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.068</td>
</tr>
<tr>
<td>GFI</td>
<td>0.893</td>
</tr>
<tr>
<td>SRMR</td>
<td>0.066</td>
</tr>
<tr>
<td>NFI</td>
<td>0.914</td>
</tr>
<tr>
<td>TLI</td>
<td>0.935</td>
</tr>
</tbody>
</table>

#### 6.3 Test for Common Method Bias

We employed various techniques to test for common methods bias. First, we assured participants that their responses would remain anonymous as Podsakoff et al. (2003) recommend. Then, we conducted different statistical tests. Initially, we compared responses from early respondents with late respondents on all constructs. The analysis revealed no statistically significant differences between the early and late responses. Subsequently, we conducted the Harman’s single-factor test on all constructs to demonstrate that common method bias due to a single response did not pose a significant issue (Podsakoff et al., 2003).
Significant common method bias exists if a single factor accounts for most of the covariance in the latent constructs. We also checked whether any two constructs had extremely strong correlations (> 0.90) by examining the correlation matrix (Pavlou & Fygenson, 2006). Methodological biases can cause spurious covariance that might inflate the correlation between measures (Campbell & Fiske, 1959). Table 5 shows that no correlation coefficients exceeded 0.9. The highest correlation coefficient was 0.59. Based on these results, we can conclude that methodological bias does not distort our conclusions.

7 Discussion

In this study, we assessed the impact that technological and individual motivational factors have on students’ engagement with using a publisher-designed Web-based assessment platform. We built our model on the MTM (Sundar et al., 2012). The data supported our hypotheses and the MTM.

Our data supports the classical influence that SDT factors have on motivation. Thus, competence (H1: $\beta = 0.57$) and autonomy (H2: $\beta = 0.48$) influenced engagement. Liu et al. (2022) argued that motivation and engagement relate to each other. Our results suggest that greater competence and autonomy perceptions lead to greater engagement.

The data also supported our hypotheses on the relationships between feedback and competence (H3a: $\beta = 0.17$) and between feedback and autonomy (H3b: $\beta = 0.28$). Researchers have always considered feedback a crucial factor impacting students’ achievement, motivation, and knowledge (Wang et al., 2008) because it helps students correct misconceptions, recreate and validate knowledge, improve academic performance, and enhance motivation. Previous research has found that feedback influences self-esteem and self-efficacy (Pintrich & Schunk, 2002) and helps increase performance because individuals become motivated to set higher goals for their tasks. The extant literature has not assessed what impact feedback has on competence and autonomy. Our findings showed that feedback can influence motivational factors. Reliable, positive, and fair feedback can help students improve their skills and autonomy. Thus, to improve students’ motivation, platforms should provide clear and reliable feedback.

We also found evidence that functionality influences competence (H4a: $\beta = 0.59$) and autonomy (H4b: $\beta = 0.65$). These motivational factors can, in turn, influence engagement. Our results indicate that platforms with advanced and various functionalities help engender higher competence in students because well-designed platforms allow for easier learning and give students control over how they use the platform in a way that best fits them. Our results concur with Sørebø et al.’s (2009) results that users experienced higher autonomy when searching for supporting material on YouTube in terms of initiative, responsibility, self-confidence, and decision-making. In our case, we found that students seem to have more self-confidence and autonomy when a platform offers several resources that make it easy for them to find the resources they need quickly and efficiently.

The data also supported our hypothesis on the relationship between response and competence (H5a: $\beta = 0.20$) and between response and autonomy (H5b: $\beta = 0.13$). In their study, Baru et al. (2020) found that students showed excitement when using technology and, in their feedback, mentioned that the technology triggered their autonomy. Our results empirically validate this relationship, which the literature has also not assessed previously. This finding indicates that students can achieve more autonomy when platforms respond quickly to their needs. This finding has particular relevance for asynchronously delivered courses that typically require students to have some independence and autonomy.

Our results also suggest that quick and responsive systems contribute to users’ sense of competence since it helps them feel some they are achieving, capable, and in control of their study.

7.1 Implications

7.1.1 Implications for Research

By identifying various determining factors that contribute to students’ engagement in this paper, we make a vital contribution to theory and practice. Many publishers have built various Web-based assessment platforms based on the many innovations in education technology over the past decade to aid instructors in evaluating students’ knowledge. However, few research studies have assessed the main factors that influence how students perceive these platforms. In this paper, we explore the underlying factors that affect students’ engagement with these e-learning platforms and related activities. To do so, we use theoretical models based on well-tested prior studies (namely, the SDT) and empirically assess the MTM. The MTM...
serves as the overarching theory that suggests that a system’s technological features can trigger an individual’s motivational and psychological needs for competence, autonomy, and relatedness (Sundar et al., 2012). The MTM places the SDT factors in the middle as intermediaries between technological factors and engagement. We adapted this model by identifying the important technology factors that relate to Web-based assessment platforms (namely feedback, functionality, and response) and by using the two SDT factors autonomy and competence. We examined the interrelationships between these factors and their impacts on students’ engagement in using Web-based assessment platforms. This paper elucidates that SDT can play a mediating role if one incorporates it into a larger model. Researchers have not examined many of these relationships. Other researchers should replicate our study to validate our results.

7.1.2 Implications for Practice

Among the groups who might benefit from our findings in this paper include IT developers, publishers, instructional designers, and university administrators. Based on our results, one cannot ignore technological, motivational, and individual factors when it comes to students’ engagement with Web-based assessment platforms. Thus, IT professionals should pay close attention to the factors that influence a student’s engagement with a Web-based assessment platform and consider them in determining the product’s ultimate success. Moreover, to continuously improve performance, practitioners should develop high-quality feedback tools that can offer students personalized feedback.

To use these platforms, students also need to acquire competency and technical skills. Thus, institutions need to provide students with the necessary technological training. Additionally, publishers and programmers must prepare students for all technical difficulties that they may encounter during the learning process by providing videos and step-by-step instructions to guide them through the material. During these videos, students need to be made aware of the different functionalities that these platforms have, which should help in their studies.

7.2 Limitations and Future Research

Despite making significant contributions, the paper has shortcomings that we must acknowledge. These limitations offer opportunities for future research. To begin, we collected a sample from students in the midwestern part of the United States. Other researchers may need to validate our model to confirm whether the results generalize to other settings. We would gain better insights into the factors affecting students’ engagement with Web-based assessment platforms by validating this model in other countries. This study outlines a model and hypotheses that researchers could mimic in future studies for other universities. In addition, we focused on developing a parsimonious research model to emphasize the associations among the main constructs. We also followed the MTM model. For this reason, we did not assess all possible relationships in the model, especially those between technological factors and engagement.

Furthermore, we focused on the interaction between students and Web-based assessment platforms and, thus, used only two factors in the SDT (i.e., competence and autonomy). Researchers might broaden our research model in the future to include relatedness, a third element in the SDT. Lastly, we explored students’ engagement with the Web-based assessment platform “Connect”. Future research could examine competitor platforms and compare the results to validate the findings of this paper.

8 Conclusion

These days, publishers often promote their Web-based assessment platforms and institutions encourage faculty to adopt them. Few studies have examined how students perceive Web-based assessment platforms that publishers design. Thus, in this study, we explore the influence that technological factors (i.e., functionality, response, and feedback) have on students’ motivation and engagement. Accordingly, this study addresses a gap in the current literature regarding the primary factors that influence students’ engagement with such e-learning technology platforms. We collected data from a public university in the Midwest part of the United States and explored new relationships that the existing literature has not previously examined, which includes the relationships in the MTM, a framework from the health IS domain.
References


Kuh, G. D., Kinzie, J., Cruce, T., Shoup, R., & Gonyea, R. M. (2007). Connecting the dots: Multi-faceted analyses of the relationships between student engagement results from the NSSE, and the institutional practices and conditions that foster student success. *Indiana University Center for Postsecondary Research.*


Appendix A:

Engagement (Webster & Ahuja, 2006)
Connect keeps me totally absorbed in reading.
Connect holds my attention.
Connect is engaging.

Autonomy (Sørebø et al., 2009)
I feel a certain freedom of action when using Connect.
I have certain freedom to pick what section to study when using Connect.
I have certain freedom to pick what activity to do when using Connect.

Competence (Sørebø et al., 2009)
When I have used Connect for a while, I feel pretty competent.
I am pretty skilled at using Connect.
I feel very competent with my performance when using Connect.

Feedback (Self-developed based on Lizzio & Wilson, 2008)
Connect provides me with useful feedback.
The feedback process in Connect is fair and just.
The feedback in Connect indicates key things that I could focus on to improve.
The feedback in Connect poses questions about the topic that made me think.

System response (Pituch & Lee, 2006)
When you are using Connect, the response is fast.
In general, the response time of Connect is consistent.
In general, the response time of Connect is reasonable.

System functionality (Pituch & Lee, 2006)
Connect offers flexibility in learning as to time and place.
Connect offers multimedia (audio, video, and text) types of course content.
Connect provides a means for taking tests and turning in assignments.
Connect can present course material in a well-organized and readable format.
About the Authors

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