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Technology adoption in higher education: an analysis of web usage mining in public-facing websites

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Abstract

With the 2026 enrollment cliff ever approaching, it is important for higher education institutions to ensure their public facing websites take advantage of technologies that improve their performance and user satisfaction. Web usage mining, the process of analyzing the usage patterns of website users to gain insights into the users' needs, has been researched extensively in both industry and higher education. Higher education has successfully used web usage mining to analyze e-learning platforms and other student focused applications to improve learning outcomes, however, research about the adoption of web usage mining technologies in higher education public facing websites is lacking. This is surprising as these websites are typically used for recruitment/marketing purposes. This study addresses the lack of research by working to answer the research question, what factors influence the adoption of web usage mining technologies in higher education websites? Combining the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model and Technology Organization Environment (TOE) framework, a survey instrument is created with the data collected used to both validate the model and answer the research question.

Keywords: web usage mining, higher education websites, technology adoption, enrollment cliff, UTAUT2, TOE.

Introduction

Despite the widespread adoption of web usage mining technologies across industry websites, especially for e-commerce (Dhandi & Chakrawarti, 2016), the adoption of web usage mining technologies in higher education (HE) websites is unknown. Web usage mining (WUM) is a data mining technique which analyzes website usage data. The vast majority of data mining in HE focuses on systems for teaching and learning (Kleftodimos & Evangelidis, 2013). However, data mining HE public-facing websites typically used for marketing/recruitment, is also of value. Understanding the usage patterns of a site can help discern knowledge of users' interests and navigational patterns, which can be used to cater to the users' needs (A. Kumar et al., 2022). With the ever-looming enrollment cliff (Campion, 2020, 2022; Schuette, 2023), the use of WUM technologies within HE institutions' public facing websites can enhance prospective students' experience, leading to a competitive recruiting advantage.

The lack of research into the adoption of WUM technologies in HE websites lead to the following research question: What factors influence the decision to adopt WUM technologies in HE institutions' public facing websites? Following a quantitative approach, a model for analyzing technology adoption in higher education was developed to address this question. The model is based on the Extended Unified Theory of

Acceptance and Use of Technology (UTAUT2) model (Venkatesh et al., 2012) and the Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990).

This study provides an overview of technology adoption in HE, provides a summary of WUM, and presents the model for evaluating WUM technology adoption in HE along with the subsequent hypotheses. The model and survey data are evaluated using partial least squares structured equation modelling (PLS-SEM). Lastly, there is a discussion of the data analysis, hypotheses results, and future work for this research.

Background

As the world continues to evolve technologically, HE institutions need to keep pace with technological advances to ensure students, faculty, and staff are offered the same level of online/digital experience they have outside of HE. Because of this, technology adoption in HE has become a key research field by many information systems scholars (Salloum et al., 2019). The explosion of research into areas such as artificial intelligence, data mining, machine learning, cloud computing, and internet of things (IoT) has caused an uptick in the speed of new technology developments. The utilization of modern information and communication technologies, especially for teaching and learning, is very important for HE institutions (Arkorful & Abaidoo, 2015). Large portions of research into HE technology adoption examine the adoption of knowledge management systems, e-learning systems, mobile technologies, and other learner-facing technologies (Arkorful & Abaidoo, 2015; King & Boyatt, 2015; Marques et al., 2011; Sailong et al., 2020; Zoleixa et al., 2020). For many of these systems, increasing engagement and improving learning outcomes are the most desired results of adopting a new technology in HE. However, HE institutions also need to ensure prospective students' needs are being met. This is especially important due to an anticipated drop in college enrollments in 2026, known in HE as the enrollment cliff, thanks in part to a drop in birthrates during the 2008 recession (Campion, 2020, 2022). Ensuring their public facing websites provide the best experience possible for prospective students should be a primary focus for HE institutions.

Web Usage Mining (WUM)

Web usage mining (WUM) is an application of data mining techniques on web log data in order to understand the who, what, and how of those using a website (A. Kumar et al., 2022). A 2020 study showed the primary sources of web log data used for WUM are server logs, client logs, and proxy logs with server logs being the most widely used source (Van Aartsen et al., 2020). Once the web log data is collected and cleaned, there are three additional processes used to complete an analysis of the data: clustering, classifying, and association mining. Clustering is the process of grouping like data together (Jain et al., 2017). In the case of website data, this could be users with similar browsing patterns or pages containing similar content. Classification is the process of mapping data item sets into predefined classes, each with its own characteristics defined by the choice of features and extracted features (Jain et al., 2017). Using a university's online bookstore as an example, a shopper may be classified as a *"Dad of [insert college name]"* shirt purchaser and a male based on items in their online shopping cart. Association rule mining determines if a relationship exists between various data entities (A. Kumar et al., 2022). Reusing our bookstore example, an association rule the online university bookstore purchasing pattern might say: *"Purchase: Dad Shirt, Gender: Male => Purchase: University Coffee Tumbler"* which states males purchasing *"Dad of [insert college name]"* shirts have a propensity to purchase university branded coffee tumblers at the same time. Each of these processes are operationalized within various technologies.

Operationalizing WUM

WUM can be operationalized through several technologies: system improvement, personalization, recommender systems, adaptive websites, and business intelligence. Each technology has its own specific purpose but the overarching goal with each of these technologies is to improve the user experience. As it relates to HE institutions' public facing websites, the goal is to ensure prospective students can find any information they need with as little effort as possible on their part in an attempt to positively influence the prospective students' decision to apply to the HE institution (Ishak et al., 2020).

Systems improvement technologies that utilize WUM are designed to improve website performance, such as using web resource prediction to decrease page load times. Web resource prediction is a way to predict the web resources, or set of resources, a user will request next based on previously requested resources and the browsing patterns of like users. Web resources include, but are not limited to, web pages, images, videos, and stylesheets. Web resource prediction is a useful technique because it allows web administrators to pre-cache web resources prior to a user requesting them, allowing the page to load faster (A. V. S. Kumar, 2017). Another reason web resource prediction is useful is it can reduce the number of unwanted resources a user has to visit to find the specific content they are looking for, increasing the likelihood they will stay engaged on the website for a longer period.

From its early days, personalization has been thought of as the pinnacle achievement for many web applications, especially those in e-commerce (Srivastava et al., 2000). The process of personalization is useful for website users and improving their experience. Personalization uses the WUM outcomes to display content to the user based on the user's interests (Suadaa, 2014). Personalization is not limited just to users' interests; it can also be based on other factors like geolocation or time of day. An example of geolocation-based personalization is automatically adjusting the visual density of information displayed on the site. In the United States, users prefer websites to have less dense user interfaces (UI) with limited external links and lower information load, whereas in China, users prefer a more visual compact/dense UI with higher information loads and more external links (Liu et al., 2020).

Much like personalization, recommender systems present users with additional content based on their historical data and other variables (Herath & Jayaratne, 2017). The creation of recommender systems is one of the most researched areas of WUM (Van Aartsen et al., 2020) and differ from personalization in that the user is requesting the information being provided. For example, a student may be registering for the next semester's courses. Based on the courses they have already taken, the major they are enrolled in, historical data of similar students, and other factors, the recommender system will provide them with a list of courses they are required to take as well as a list of electives they may enjoy.

Adaptive websites are websites that adapt to changes based on the outcomes of web usage mining (Herath & Jayaratne, 2017). Modifications to website navigation, usability, or accessibility are a few examples of items on websites that may be adjusted. For example, imagine the WUM outcomes reveal that over the past 3 days, 75% of users browsing the university website are looking for information on the upcoming graduation ceremony. An adaptive website may adjust the menu navigation to include a direct link to the graduation information page, so users no longer need to search for it - thus improving the user experience. The overall goal of an adaptive website is to respond to users' needs and wants to make the site run more effectively for the user (Bhargav & Bhargav, 2014).

Lastly, WUM technologies utilized for business intelligence aid in understanding users' needs, allowing improved customer attraction, customer retention, and marketing/advertising (A. Kumar et al., 2022). Business intelligence combines data from many sources, including databases, analytical tools, and applications, and processes the raw data and collection of existing information into knowledge used to support business decisions (Suharjito et al., 2016). Website analytic tools often make use of WUM to classify users and uncover website usage patterns with the overarching goal of measuring the effectiveness of the website. More specifically for HE institutions, the effectiveness of their public facing websites at influencing prospective students' decisions to apply to the university.

Model Development

There are numerous models and frameworks used in information systems (IS) covering both individual and organizational aspects of technology acceptance and technology adoption. These include the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Diffusion of Innovation (DoI), Unified Theory of Acceptance and Use of Technology (UTAUT), Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), and Technology-Organization-Environment (TOE) (Lai, 2017; Taherdoost, 2018). Depending on the specific WUM technology implementation, the choice to adopt a WUM technology can be both an individual and organizational decision. As such, the UTAUT2 model was chosen for its focus on the individual aspects of technology adoption, while the TOE framework was chosen to frame the organizational aspects of technology adoption. The proposed model (**Error! Reference source not found.**) and subsequent hypotheses formed for this r esearch combine the elements of TOE and UTAUT2 to explain both the organizational and individual aspects of WUM adoption in HE.

Technology-Organization-Environment (TOE) framework

The Technology-Organization-Environment (TOE) framework is an organization-level theory with three different elements used to explain an organization's decision to adopt a technology (Baker, 2012). Those elements are the technology context, organization context, and environment context. The technology context includes all technologies relevant to the firm, including those already in use at the firm and those available in the marketplace but not in use (Baker, 2012). The organization context is concerned with the characteristics and resources of the firm (Baker, 2012). The environment context encompasses the structure of the industry, presence or absence of technology service providers, and regulatory environment. The three contexts in TOE present "both constraints and opportunities for technological innovation" (Tornatzky et al., 1990) and these elements influence the level of innovation or adoption of innovative technologies (Baker, 2012).

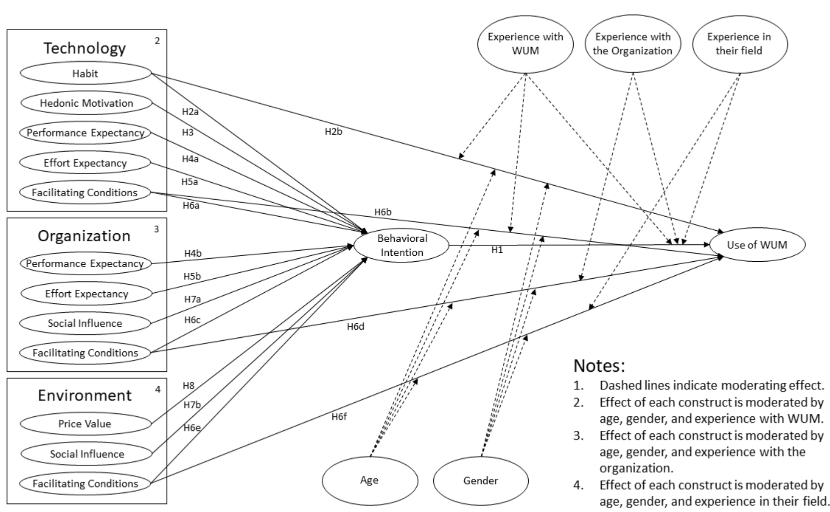

Figure 1 - WUM Technology Adoption in HE Websites Model

Behavior Intention and Use

In UTATU2, the two primary constructs used to evaluate technology adoption are Behavioral Intention (BI) and Use (USE). BI is a measure of the intention to adopt the technology being explored (Venkatesh et al.,

2012). USE is a measure of the actual adoption or continuing adoption of the technology being explored (Venkatesh et al., 2012). Within the UTAUT2 model, BI also has a direct relationship with USE and is moderated by experience. For the purposes of this study, BI and USE are used to measure HE institutions' intention to adopt and the actual adoption of WUM technologies respectively and forms the following hypothesis:
H1: there is a relationship between the behavioral intention and actual use of WUM technologies in HEI public facing websites.

Habit
Habit is an individual aspect of technology adoption defined in UTAUT2 as a measure of the tendency of people to use a technology instinctively or automatically due to their prior usage of said technology (Venkatesh et al., 2012). Habit has been shown to have a direct relationship between both BI and USE, with the relationships being moderated by age, gender, and experience. For this study, habit (Tech_HAB) is grouped under the Technology context and has a direct relationship with both BI and USE. The following hypotheses are formed:

H2a: there is a relationship between the technology context of habit to use and behavioral intention to use WUM technologies in HEI public facing websites.
H2b: there is a relationship between the technology context of habit to use and actual use of WUM technologies in HEI public facing websites.

Hedonic Motivation
Within the UTUAT2 model, Hedonic Motivation is defined as measure of how enjoyable or fun a technology is to use (Venkatesh et al., 2012). Hedonic Motivation has been shown to have a direct relationship with individuals' intention to use a technology. For this study, Hedonic Motivation (Tech_HM) is grouped under the Technology context and has a direct relationship with BI and forms the following hypothesis:
H3: there is a relationship between the technology context of hedonic motivation of WUM technologies and behavioral intention to use WUM technologies in HEI public facing websites.

Performance Expectancy
Performance expectancy is referred to in UTAUT2 as the benefit that can be obtained from utilizing a particular technology (Venkatesh et al., 2003). Looking at performance expectancy from the Technology context, performance expectancy (Tech_PE) is a measure of an individual's belief using WUM technologies will help them complete their goals (Venkatesh et al., 2003). Performance expectancy is also explored under the Organization context (Org_PE) and is a measure of an individual's belief their HE institution will achieve its goals by adopting WUM technologies in their public facing websites. The following hypotheses are formed:

H4a: there is a relationship between the technology context of performance expectancy and behavioral intention to use WUM technologies in HEI public facing websites.
H4b: there is a relationship between the organization context of performance expectancy and behavioral intention to use WUM technologies in HEI public facing websites.

Effort Expectancy
UTAUT2 defines Effort Expectancy as the degree of ease associated with the use of a technology (Venkatesh et al., 2012). Within the Technology context, effort expectancy (Tech_EE), measures how difficult or easy an individual believes WUM technologies are to learn and use. Looking at effort expectancy from the Organization context, effort expectancy (Org_EE) measures an individual's belief in

how easy or difficult WUM technologies are to learn and use for others within their institution. The following hypotheses are formed:

H5a: there is a relationship between the technology context of effort expectancy and behavioral intention to use WUM technologies in HEI public facing websites.
H5b: there is a relationship between the organization context of effort expectancy and behavioral intention to use WUM technologies in HEI public facing websites.

Facilitating Conditions

As defined within UTAUT2, Facilitating Conditions refers to an individual's perceptions of the level of resources and support available for using a particular technology, as well as the technology's compatibility with other technologies the individual is already using (Venkatesh et al., 2012). Under the Technology context, facilitating conditions (Tech_FC) is a measure of the compatibility of WUM technologies with other technologies an individual uses in their institution. Tech_FC has a direct relationship with BI and with USE. From the Organization context, facilitating conditions (Org_FC) is a measure of individual's belief their institution has the resources available to implement and use WUM technologies within their public facing websites. Org_FC has a direct relationship with BI and with USE. Facilitating conditions are also explored from the Environment context, where facilitating conditions (Env_FC) is a measure of the external aid/support resources available for using WUM technologies within the HEI. Env_FC has a direct relationship with BI and with USE. The following hypotheses are formed:
H6a: there is a relationship between the technology context of facilitating conditions and behavioral intention to use WUM technologies in HEI public facing websites.
H6b: there is a relationship between the technology context of facilitating conditions and actual use of WUM technologies in HEI public facing websites.
H6c: there is a relationship between the organization context of facilitating conditions and behavioral intention to use WUM technologies in HEI public facing websites.
H6d: there is a relationship between the organization context of facilitating conditions and actual use of WUM technologies in HEI public facing websites.
H6e: there is a relationship between the environment context of facilitating conditions and behavioral intention to use WUM technologies in HEI public facing websites.
H6f: there is a relationship between the environment context of facilitating conditions and actual use of WUM technologies in HEI public facing websites.

Social Influence

UTAUT2 defines Social Influence as an individual's belief that important others (ex. family, co-workers, upper management, etc.) believe the individual should use a particular technology (Venkatesh et al., 2012). For this study, Social Influence is explored under the Organization context (Org_SI) and Environment (Env_SI). Org_SI is a measure of support from upper management and other departments within the HE institution for adopting WUM technologies within the public facing websites. Env_SI is a measure of the use of WUM technologies by external people and other HE institutions. Both Org_SI and Env_SI have direct relationships to BI. The following hypotheses are formed:
H7a: there is a relationship between the organization context of social influence and behavioral intention to use WUM technologies in HEI public facing websites.
H7b: there is a relationship between the environment context of social influence and behavioral intention to use WUM technologies in HEI public facing websites.

Price Value

Price Value refers to an individual's belief that the price of a technology is reasonable and is a good value (Venkatesh et al., 2012). For this study, price value (Env_PV) is grouped under the Environment context as price is viewed as an external factor. Env_PV is a measure of an individual's belief that WUM technologies used within HEI public facing websites are a good value and are reasonably priced. Env_PC has a direct relationship with BI and forms the following hypothesis:
H8: there is a relationship between price value and behavioral intention to use WUM technologies in HEI public facing websites.

Moderating Effects

As with UTAUT2, Age (AGE), Gender (GEN), and Experience have moderating effects (Venkatesh et al., 2012). The definition of experience is pulled from UTAUT and is defined as the level of experience an individual has with the particular technology they are being asked to use (Venkatesh et al., 2003, 2012). For the purposes of this study, experience is expanded to encompass additional aspects of experience as they relate to organization and environment. To capture what experience means in the TOE contexts, experience is divided into three distinct experience areas: Experience with WUM Technologies (EXPINWUM), Experience within the Organization (EXPINORG), Experience in their Field (EXPINFIELD). EXPINWUM is a measure of the number of years of experience the individual has with WUM. EXPINORG is a measure of the number of years of experience the individual has with the HE institution. EXPINFIELD is a measure of the number of years of experience the individual has within their field.

Methodology and Analysis

This research focuses on answering the research question, what factors influence the decision to adopt WUM technologies in HE institutions' public facing websites? Following the approach used by Venkatesh, L. Thong, and Xu (Venkatesh et al., 2012), a survey was developed to collect data and partial least squares structural equation modeling (PLS-SEM) was used to empirically test the hypotheses. To avoid issues related to survey fatigue, such as low response rate (North & Giddens, 2013) and mindless response behavior (Drolet & Morrison, 2001), the survey was developed to measure each construct with two items. Previous work has established there is minimal change in predictive validity in single-item versus multi-item measures of the same construct (Bergkvist & Rossiter, 2007). According to Drolet and Morrison, the more items used to measure a construct leads to a reduction in the overall reliability of the construct (Drolet & Morrison, 2001). The survey was administered through an email survey campaign utilizing Google Forms (Google, 2023) and an online survey platform, Pollfish (Pollfish, 2023). The target population for the study was HE professionals responsible for the public website(s) at HE institutions located in the Midwest region of the United States (US) as defined by the US Census Bureau (U.S. Census Bureau, 2000). The inverse root square method was used to determine the minimum sample size. Based on previous studies, it is expected the minimum path coefficient will fall in the range of 0.11-0.20 (Evans 2013; Khechine et al. 2014; Stigzelius n.d.; Venkatesh et al. 2003; Venkatesh, L. Thong, and Xu 2012). Given the inputs *pmin* of 0.11 to 0.20 and a significance level of 0.05, the minimum sample size for the study is 155. The email survey campaign resulted in 21 responses while the Pollfish survey resulted in 266 responses. Removing responses with incomplete or invalid data left 156 responses remaining to be used in the final data analysis, which is above the minimum sample size threshold.

The model was assessed using PLS-SEM. The PLS-SEM computations were completed using SmartPLS 4, a popular structured equation modeling software (Ringle et al., 2022). SmartPLS 4 provides numerous results used to assess a model using PLS-SEM, including factor loadings, Cronbach's Alpha, composite reliability, average variance extracted, Heterotrait-monotrait, coefficient of determination, standardized root mean square residual, and path coefficients.

Measurement Model Assessment

When evaluating PLS-SEM results, the first step is to examine the measurement models for measure reliability and construct reliability (Hair et al., 2019). Measure reliability is achieved by reviewing the outer loadings of the measure on the construct it informs. Outer loading values higher than 0.708 provide acceptable measure reliability as they indicate the construct explains more than 50 percent of the measure's variance (Hair et al., 2019). **Error! Reference source not found.** shows all measures have an outer loading a bove 0.708, thus measure reliability is confirmed.

Table 1: Demographics

University Type	Count	Percentage
Graduate	51	32.7%
Baccalaureate	53	34.0%
Associates	52	33.3%

WUM Technology Usage	Count	Percentage
Content/Experience Personalization	62	39.7%
Product/Content Recommendation	61	39.1%
Adaptive Site Modification	58	37.2%
System Improvement	64	41.0%
Business Intelligence	67	42.9%

Age	Count	Percentage
< 20	6	3.8%
20-29	32	20.5%
30-39	37	23.7%
40-49	33	21.2%
50-59	35	22.4%
60+	13	8.3%

Gender	Count	Percentage
Female	85	54.5%
Male	71	45.5%

Experience with WUM Technologies	Count	Percentage
< 1 year	21	13.5%
1-3 years	32	20.5%
3-5 years	38	24.4%
5-10 years	28	17.9%
10-20 years	22	14.1%
20+ years	15	9.6%

Experience in their Organization	Count	Percentage
< 1 year	15	9.6%
1-3 years	28	17.9%
3-5 years	39	25.0%
5-10 years	33	21.2%
10-20 years	23	14.7%
20+ years	18	11.5%

Experience in their Field	Count	Percentage
< 1 year	16	10.3%
1-3 years	23	14.7%
3-5 years	33	21.2%
5-10 years	26	16.7%
10-20 years	30	19.2%
20+ years	28	17.9%

Table 2: Measurement Model Results

Construct	Measurement Reliability	Construct Reliability	Construct Validity	Discriminant Validity
	Outer Loadings > 0.708	ρ_a	**AVE**	**HTMT < 0.85**
Tech_HAB	Yes	0.811	0.806	Yes
Tech_HM	Yes	0.735	0.782	Yes
Tech_PE	Yes	0.740	0.791	Yes
Tech_EE	Yes	0.870	0.838	Yes
Tech_FC	Yes	0.720	0.781	Yes
Org_PE	Yes	0.836	0.829	Yes
Org_EE	Yes	0.850	0.830	Yes
Org_FC	Yes	0.778	0.818	Yes
Org_SI	Yes	0.802	0.834	Yes
Env_FC	Yes	0.789	0.825	Yes
Env_PV	Yes	0.832	0.827	Yes
Env_SI	Yes	0.798	0.831	Yes
BI	Yes	0.834	0.841	Yes

Assessing construct reliability and validity is the next phase of the PLS-SEM analysis (Hair et al., 2019). Composite reliability (ρ_c) has become a preferred alternative to Cronbach's alpha for assessing construct reliability (Garson, 2016) due to items being unweighted in Cronbach's alpha produces a less precise measure of reliability (Hair et al., 2019). However, ρ_c produces reliability values that are too high, with the real reliability values lying between Cronbach's alpha and ρ_c. Dijkstra and Henseler (2015) proposed ρ_a as an alternative that typically lies between Cronbach's alpha and composite reliability. For ρ_a, values between 0.70 and 0.90 are considered good (Garson, 2016). Values higher than 0.90 may indicate items are redundant, reducing construct reliability (Hair et al., 2019). **Error! Reference source not found.** shows t he values of ρ_a for all constructs fall between 0.70 and 0.90, thus confirming construct reliability.

Construct validity is assessed using the average variance extracted (AVE). AVE measures the extent to which a construct converges to explain the variance of its items (Hair et al., 2019). Acceptable AVE values are 0.50 and higher. **Error! Reference source not found.** displays the AVE result for each construct, all o f which are above the 0.50 threshold needed to confirm convergent validity.

The last step for assessing the measurement model is to ensure discriminant validity does not exist within the constructs. The heterotrait-monotrait (HTMT) ratio of the correlations is used to assess the constructs for discriminant validity. HTMT is defined "as the mean value of the indicator correlations across constructs (i.e., the heterotrait–heteromethod correlations) relative to the (geometric) mean of the average correlations for the indicators measuring the same construct (i.e., the monotrait–heteromethod correlations)" (Hair et al., 2021). Values below 0.9, or more conservatively 0.85 (Henseler et al., 2015), suggest discriminant validity problems are not present (Hair et al., 2021). **Error! Reference source not found.** shows a s ummarization of the HTMT results analysis, confirming all HTMT results fell below the more conservative 0.85 threshold. This confirms discriminant validity is not present among the constructs.

Structural Model Assessment

With the measurement model assessment proving satisfactory, an evaluation of the structural model was completed. Standard assessment criteria include the coefficient of determination (R^2), model fit, and the statistical significance and relevance of the path coefficients (Hair et al., 2019).

R^2 is a measure of the explanatory power of the model as it measures the variance explained in each of the endogenous constructs (Hair et al., 2019). Values for R^2 range from 0 (low explanatory power) to 1 (high explanatory power). Values at or above the cutoffs 0.19, 0.33, and 0.67 can be considered weak, moderate, and substantial respectively (Garson, 2016). Table 3 displays the R^2 values for BI and USE. With an R^2 of 0.871, BI is considered to have substantial explanatory power. USE has an R^2 of 0.575 representing a moderate explanatory power.

Table 3: R^2 Results

	R^2
BI	0.871
USE	0.575

In PLS-SEM, one approach to assessing a model's fit, is calculating the standardized root mean square residual (SRMR). The SRMR measures the difference between the observed and model-implied correlation matrices (Garson, 2016). Because SRMR reflects the magnitude of those differences, a lower SRMR indicates a better fit (Garson, 2016). A model with a SRMR of less than 0.08 is considered to have good fit. Table 4 shows the SRMR falls below the 0.08 threshold, thus the model is a good fit.

Table 4: Standardized Root Mean Square Residual (SRMR)

	Saturated model	Estimated model
SRMR	0.054	0.060

Path coefficients are a standardized measure of the changes in the dependent variable values that are associated with the changes in the independent variable and are assessed by reviewing both their value and significance (Hair et al., 2019). The significance of a path coefficient is calculated using bootstrapping. Because the values are standardized, the values will fall between -1 and 1. The closer the absolute value is to 1, the stronger the effect while the closer the value is to 0, the weaker the effect (Garson, 2016). Path coefficients can also interpret the indirect effect of one or more intervening constructs, which is useful for assessing moderating effects (Nitzl, 2016). Table 5 displays the path coefficient values for all independent variables and their effects on BI and USAGE.

Table 5: Path Coefficients

Path	BI	USAGE
AGE_T	-0.046	0.043
AGE_T x GEN	0.048	-0.071
BI		-0.021
BI x EXPINFIELD		0.066
BI x EXPINORG		-0.157*
BI x EXPINWUM		-0.104*
Env_FC	-0.052	-0.05
Env_FC x AGE_T	0.035	-0.101
Env_FC x AGE_T x EXPINFIELD	0.142*	0.103*
Env_FC x AGE_T x EXPINFIELD x GEN	-0.04	0.043
Env_FC x AGE_T x GEN	0.036	-0.026
Env_FC x EXPINFIELD	0.05	0.086
Env_FC x EXPINFIELD x GEN	-0.016	-0.009
Env_FC x GEN	0.074	-0.02
Env_PV	0.067	
Env_PV x AGE_T	0.041	
Org_FC x EXPINORG	-0.04	0.103
Org_FC x EXPINORG x GEN	-0.065	0.041
Org_FC x GEN	-0.013	0.04
Org_PE	-0.04	
Org_PE x AGE_T	-0.061	
Org_PE x AGE_T x EXPINORG	0.008	
Org_PE x AGE_T x EXPINORG x GEN	0.781*	
Org_PE x AGE_T x GEN	-0.013	
Org_PE x EXPINORG	0.116	
Org_PE x EXPINORG x GEN	0.042	
Org_PE x GEN	-0.012	
Org_SI	-0.127	
Org_SI x AGE_T	0.082	
Org_SI x AGE_T x EXPINORG	-0.591*	
Org_SI x AGE_T x EXPINORG x GEN	-0.061	
Org_SI x AGE_T x GEN	-0.022	

Env_PV x AGE_T x EXPINFIELD	0.656**	
Env_PV x AGE_T x EXPINFIELD x GEN	0.124	
Env_PV x AGE_T x GEN	0.086	
Env_PV x EXPINFIELD	0.067	
Env_PV x EXPINFIELD x GEN	0.127	
Env_PV x GEN	0.112	
Env_SI	-0.083	
Env_SI x AGE_T	0.016	
Env_SI x AGE_T x EXPINFIELD	-0.051	
Env_SI x AGE_T x EXPINFIELD x GEN	-0.897*	
Env_SI x AGE_T x GEN	0.039	
Env_SI x EXPINFIELD	-0.094	
Env_SI x EXPINFIELD x GEN	-0.027	
Env_SI x GEN	-0.031	
EXPINFIELD	0.11	-0.016
EXPINFIELD x AGE_T	0.066	-0.104
EXPINFIELD x AGE_T x GEN	0.069	-0.012
EXPINFIELD x GEN	0.02	-0.072
EXPINORG	-0.04	0.074
EXPINORG x AGE_T	-0.013	0.021
EXPINORG x AGE_T x GEN	0.015	-0.065
EXPINORG x GEN	0.078	-0.101
EXPINWUM	-0.041	-0.063
EXPINWUM x AGE_T	-0.02	0.102
EXPINWUM x AGE_T x GEN	-0.081	-0.048
EXPINWUM x GEN	0.084	0.055
GEN	-0.109	-0.084
Org_EE	0.05	
Org_EE x AGE_T	0.045	
Org_EE x AGE_T x EXPINORG	0.027	
Org_EE x AGE_T x EXPINORG x GEN	0.176**	
Org_EE x AGE_T x GEN	0.086	
Org_EE x EXPINORG	0.087	
Org_EE x EXPINORG x GEN	0.129	
Org_EE x GEN	0.118	
Org_FC	0.098	0.071
Org_FC x AGE_T	0.101	0.059
Org_FC x AGE_T x EXPINORG	0.11	-0.054
Org_FC x AGE_T x EXPINORG x GEN	0.302*	0.162*
Org_FC x AGE_T x GEN	-0.104	0.021

Org_SI x EXPINORG	0.097	
Org_SI x EXPINORG x GEN	0.032	
Org_SI x GEN	0.016	
Tech_HAB	0.1	-0.097
Tech_HAB x AGE_T	-0.08	0.02
Tech_HAB x AGE_T x EXPINWUM	-0.029	-0.149*
Tech_HAB x AGE_T x EXPINWUM x GEN	-0.203**	0.074
Tech_HAB x AGE_T x GEN	0.026	-0.092
Tech_HAB x EXPINWUM	0.084	0.094
Tech_HAB x EXPINWUM x GEN	-0.031	0.023
Tech_HAB x GEN	0.024	0.05
Tech_HM	0.063	
Tech_HM x AGE_T	0.041	
Tech_HM x AGE_T x EXPINWUM	0.108*	
Tech_HM x EXPINWUM	-0.048	
Tech_EE	-0.124	
Tech_EE x AGE_T	-0.042	
Tech_EE x AGE_T x EXPINWUM	-0.116*	
Tech_EE x AGE_T x EXPINWUM x GEN	-0.094	
Tech_EE x AGE_T x GEN	0.008	
Tech_EE x EXPINWUM	-0.011	
Tech_EE x EXPINWUM x GEN	0.054	
Tech_EE x GEN	-0.029	
Tech_FC	0.083	0.008
Tech_FC x AGE_T	0.084	0.018
Tech_FC x AGE_T x EXPINWUM	0.078	0.052
Tech_FC x AGE_T x EXPINWUM x GEN	0.458*	0.181**
Tech_FC x AGE_T x GEN	0.076	0.079
Tech_FC x EXPINWUM	0.027	0.038
Tech_FC x EXPINWUM x GEN	0.122	0.023
Tech_FC x GEN	0.066	-0.031
Tech_PE	0.084	
Tech_PE x AGE_T	-0.045	
Tech_PE x AGE_T x EXPINWUM	-0.03	
Tech_PE x AGE_T x EXPINWUM x GEN	-0.033	
Tech_PE x AGE_T x GEN	-0.021	
Tech_PE x EXPINWUM	0.059	
Tech_PE x EXPINWUM x GEN	0.531*	
Tech_PE x GEN	0.051	

Note: * $p < 0.05$; ** $p < 0.01$

Results

The study examined five hypothetical relationships influencing the use of WUM technologies in HE institutions' public facing websites. Table 5 shows the relationship between Tech_FC and USE is both positive and significant with the relationship being moderated by AGE, EXPINWUM, and GEN, thus H6b is found to be supported. The relationship tells us the use WUM technologies increases when they are compatible with other technologies already in use within the institution, with the effect being stronger for women who are older and have more experience in WUM technologies.

Table 5 shows the relationship between Org_FC and USE is both positive and significant with the relationship being moderated by AGE, EXPINORG, and GEN, thus H6d is found to be supported. The relationship shows the use of WUM increases when an institution has the resources needed to use WUM technologies and internal knowledge support available, with the effect being increased for women who are older and more experienced with the institution. Table 5 shows the relationship between Env_FC and USE is both positive and significant with the relationship being moderated by AGE and EXPINFIELD, thus H6f is found to be supported. The relationship shows the use of WUM increases when technology support resources are available from outside of the institution, with the effect increasing as people become older and more experienced in their field. Table 5 shows the relationship between Tech_HAB and USE is negative and significant with the relationship being moderated by AGE and EXPINWUM, thus H2b is found to be supported. The relationship shows even though the use of WUM technologies may be habitual, the effect of habit on use decreases as people become older and more experienced in WUM technologies. Table 5 shows the relationship between BI and USE is negative and significant with the effect being moderated by EXPINWUM and EXPINORG, thus H1 is found to be supported. The relationship shows the intention to use WUM technologies affects the actual use of WUM technologies, but the effect decreases as people gain experience using WUM technologies and experience within their institution.

The study also examined twelve hypothetical relationships influencing the intent to use WUM technologies in HE institutions' public facing websites. As shown in Table 5, the path coefficients results reveal all twelve relationships are found to be significant with eight relationships having positive effects and four relationships having negative effects. Each of the relationships was found to be affected by two or more moderators. Assessing the hypotheses directly, *H2a*, *H3*, *H4a*, *H4b*, *H5a*, *H5b*, *H6a*, *H6c*, *H6e*, *H7a*, *H7b*, and *H8* are found to be supported.

The relationships Tech_HM, Tech_PE, Org_PE, Org_EE, Tech_FC, Org_FC, Env_FC, and Env_PV each have with BI are found to be positive. The relationship between Tech_HM and BI, as moderated by AGE and EXPINWUM, shows the intention to use WUM technologies increases when they are more enjoyable to use, with the effect increasing as people become older and more experienced with WUM technologies. The relationship between Tech_PE and BI, as moderated by GEN and EXPINWUM, shows the intention to use WUM technologies increases when using them is expected to aid in accomplishing individuals' goals, with the effect being increased for women with more experience with WUM technologies.

The relationship between Org_PE and BI, as moderated by AGE, GEN, and EXPINORG, shows the intention to use WUM technologies increases when using them is expected to aid in accomplishing a university's goals, with the effect being increasing as individuals increase in age and experience with their university, especially for women. The relationship between Org_EE and BI, as moderated by AGE, GEN, and EXPINORG, shows the intention to use WUM technologies increases when an individual believes others in their institution will find WUM technologies easy to use.

The effect increases as individuals increase in age and experience with their institution, even more so for women. The Tech_FC, Org_FC, and Env_FC relationships with BI show intention to use WUM technologies increases when they are compatible with other technologies already in use, the HE institution has resources available, and there is knowledge support available both inside and outside of the institution. The effects increase as people age and become more experienced.

The effect is also stronger for women in both Tech_FC and Org_FC. The relationship between Env_PV and BI, as moderated by AGE and EXPINFIELD, shows intention to use WUM technologies increases when individuals find the price of WUM technologies to be a good value with the effect increasing as individuals become older and more experienced in their field. Of the positive relationships, Tech_PE, Org_PE, and Env_PV are the most influential with path coefficients of 0.531, 0.781, and 0.656, respectively.

The relationships Tech_HAB, Tech_EE, Org_SI, and Env_SI each have with BI are found to be negative. The relationship between Tech_HAB and BI, as moderated by AGE, GEN, and EXPINWUM, shows intention to use WUM technologies decreases as individuals increase in age and experience with WUM technologies, with the effect being more significant for women.

The relationship between Tech_EE and BI, as moderated by AGE and EXPINWUM, shows although individuals may find WUM technologies easy to use, the intention to use WUM technologies decreases as people age and become more experienced with WUM technologies. The Org_SI and Env_SI relationships with BI, shows a decreasing effect of social influences from inside and outside the institution as individuals increase in age and experience, the with the effect being strong for women in the Env_SI and BI relationship. Of the negative relationships, Org_SI and Env_SI are the most influential with path coefficients of -0.591 and -0.897, respectively.

Along with the understanding which factors influence WUM technology use in HE institutions' websites, the study also found the use/adoption rate of the various WUM technologies is lower than anticipated. The demographic data in
The model was assessed using PLS-SEM. The PLS-SEM computations were completed using SmartPLS 4, a popular structured equation modeling software (Ringle et al., 2022). SmartPLS 4 provides numerous results used to assess a model using PLS-SEM, including factor loadings, Cronbach's Alpha, composite reliability, average variance extracted, Heterotrait-monotrait, coefficient of determination, standardized root mean square residual, and path coefficients.

Measurement Model Assessment
When evaluating PLS-SEM results, the first step is to examine the measurement models for measure reliability and construct reliability (Hair et al., 2019). Measure reliability is achieved by reviewing the outer loadings of the measure on the construct it informs. Outer loading values higher than 0.708 provide acceptable measure reliability as they indicate the construct explains more than 50 percent of the measure's variance (Hair et al., 2019). **Error! Reference source not found.** shows all measures have an outer loading above 0.708, thus measure reliability is confirmed.

Table 1 shows the rate of use of each of the five WUM application areas is less than 50%.

The result is surprising given the amount of research that has been conducted into each WUM technology (Van Aartsen et al., 2020). Using the application of WUM technologies for business intelligence as a specific example, the use/adoption rate is at 42.9% which is well below the worldwide use/adoption rate of 62.1% (W3Techs, 2024). HE institutions using WUM technologies may have a competitive advantage when recruiting new students.

Conclusion

The focus of this research was to determine the factors influencing the adoption of WUM technologies in higher education institutions' public facing websites. The research shows the factors influencing the adoption of WUM technologies are the intention to use WUM technologies, individuals' habit of using WUM technologies, the availability of technology support resources both inside and outside of the institution, and the compatibility of the WUM technologies with other technologies in use at the institution. The strongest factors influencing WUM technology adoption are intention, technology compatibility, and the availability of internal support resources, with each being more important for individuals as they age and as they gain more experience with WUM technologies and within their institution.

Behavior Intention was found to be influenced by the factors habit of WUM technology use, hedonic motivation, performance expectancy as it relates to individuals and HE institutions, effort expectancy as it relates to individuals and HE institutions, facilitating conditions which include technology compatibility and the availability of technology support resources both internally and externally, social influence from internal and external sources, and the price value. The factors with the strongest influences on the intention to adopt WUM technologies are performance expectancy, price value, and social influence, with the effects increasing in strength as individuals age and become more experienced with WUM technologies, within their HE institutions, and within their field.
The model formed by combining the TOE and UTAUT2 frameworks was proven to be useful in evaluating the adoption of WUM technologies in public facing websites at HE institutions within the Midwest region of the US. The model explains the 87.1% of the variance in the intention to use WUM technologies and explains 57.5% of the variance in WUM technology use/adoption.

The research also found a gap in WUM technology adoption within the institutions surveyed. For each of the WUM technologies explored within the research, namely system improvement, personalization, recommender systems, adaptive websites, and business intelligence, the adoption rate of each technology is below 45%. With the impending challenges universities are about to face due to the enrollment cliff, adopting WUM technologies within their public facing websites may be a way to create a competitive advantage for attracting new students. Additional research should be conducted to further explore the gap in WUM technology adoption rates and to explore if HE institutions that have adopted WUM technologies are seeing increased enrollment growth.

This research is limited by its sample and data collection methodology, reducing its generalizability, as the sample is constrained to higher education institutions in the Midwest region of the US. The research is also limited in its ability to explore the nuances between different types of HE institutions (public/private, small/medium/large, associate/bachelor/graduate degree offering) and the nuances between individual WUM technologies. Additional research should be conducted with the goal of evaluating the generalizability of the model and analyzing the differences in WUM adoption for different types of HE institutions and WUM technologies.

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